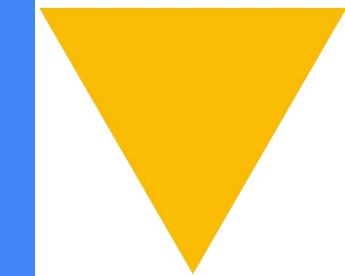


05



Advanced BigQuery Functionality and Performance

Advanced BigQuery Functionality and Performance

- 01 Analytic window functions
- 02 GIS functions
- 03 Performance considerations



Advanced BigQuery Functionality and Performance

01

Analytic window functions

02

GIS functions

03

Performance considerations



Use analytic window functions for advanced analysis

- Standard aggregations
- Navigation functions
- Ranking and Numbering functions

Example: The COUNT function (self-explanatory)

```

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



Query results [SAVE RESULTS](#) ▾ [EXPLORE WITH DATA STUDIO](#)

Query complete (13.5 sec elapsed, 1.5 GB processed)

Job information [Results](#) (selected) [JSON](#) [Execution details](#)

Row	start_station_name	end_station_name	typical_duration	num_trips
1	Borough High Street, The Borough	Bell Street , Marylebone	4320	3
2	William IV Street, Strand	Little Brook Green, Brook Green	4500	3
3	Baker Street, Marylebone	George Place Mews, Marylebone	180	95
4	Waterloo Station 2, Waterloo	Westbourne Grove, Bayswater	3240	7
5	Imperial Wharf Station	Upperne Road, West Chelsea	180	94
6	Kennington Road , Vauxhall	Westminster Bridge Road, Elephant & Castle	180	38
7	Whiston Road, Haggerston	Pitfield Street North,Hoxton	180	99
8	Gloucester Street, Pimlico	Rampayne Street, Pimlico	180	330
9	Harrington Square 1, Camden Town	Drummond Street , Euston	180	76

Some other “standard” aggregation functions

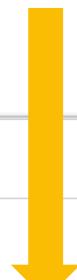
- SUM
- AVG
- MIN
- MAX
- BIT_AND
- BIT_OR
- BIT_XOR
- COUNTIF
- LOGICAL_OR
- LOGICAL_AND

[More SQL aggregate functions](#)

Example: The LEAD function returns the value of a row n rows ahead of the current row

```

SELECT
    start_date,
    end_date,
    bike_id,
    start_station_id,
    end_station_id,
    LEAD(start_date, 1) OVER(PARTITION BY bike_id ORDER BY start_date ASC ) AS
next_rental_start
FROM
    `bigquery-public-data`.london_bicycles.cycle_hire
WHERE
    bike_id = 9
  
```



Query results [SAVE RESULTS](#) ▾ [EXPLORE WITH DATA STUDIO](#)

Query complete (2.0 sec elapsed, 926.1 MB processed)

Job information [Results](#) [JSON](#) [Execution details](#)

Row	start_date	end_date	bike_id	start_station_id	end_station_id	next_rental_start
1	2015-01-04 14:03:00 UTC	2015-01-04 15:17:00 UTC	9	176	176	2015-01-05 09:04:00 UTC
2	2015-01-05 09:04:00 UTC	2015-01-05 09:22:00 UTC	9	176	106	2015-01-05 18:17:00 UTC
3	2015-01-05 18:17:00 UTC	2015-01-05 18:32:00 UTC	9	106	286	2015-01-06 16:23:00 UTC
4	2015-01-06 16:23:00 UTC	2015-01-06 16:30:00 UTC	9	286	99	2015-01-06 17:08:00 UTC
5	2015-01-06 17:08:00 UTC	2015-01-06 17:14:00 UTC	9	99	49	2015-01-06 17:51:00 UTC
6	2015-01-06 17:51:00 UTC	2015-01-06 18:02:00 UTC	9	49	345	2015-01-06 18:58:00 UTC
7	2015-01-06 18:58:00 UTC	2015-01-06 19:13:00 UTC	9	345	603	2015-01-07 08:30:00 UTC
8	2015-01-07 08:30:00 UTC	2015-01-07 08:48:00 UTC	9	603	112	2015-01-07 16:44:00 UTC
9	2015-01-07 16:44:00 UTC	2015-01-07 16:58:00 UTC	9	465	67	2015-01-07 17:05:00 UTC

Some other navigation functions

- NTH_VALUE
- LAG
- FIRST_VALUE
- LAST_VALUE

[More SQL navigation functions](#)

Example: The RANK function returns the integer rank of a value in a group of values

```
WITH
  longest_trips AS (
    SELECT
      start_station_id,
      duration,
      RANK() OVER(PARTITION BY start_station_id ORDER BY duration DESC) AS
      nth_longest
    FROM
      `bigquery-public-data`.london_bicycles.cycle_hire )
  SELECT
    start_station_id,
    ARRAY_AGG(duration
    ORDER BY
      nth_longest
    LIMIT
      3) AS durations
  FROM
    longest_trips
  GROUP BY
    start_station_id
```

Query results  SAVE RESULTS EXPLORE WITH DATA STUDIO

Query complete (7.0 sec elapsed, 370.1 MB processed)

Job information Results JSON Execution details

Row	start_station_id	durations
1	4	457380
		406140
		405300
2	11	872400
		511680
		312420
3	21	2238840
		1188000
		587340

Example: RANK() Function for aggregating over groups of rows

firstname	department	startdate
Andrew	1	1/23/1999
Jacob	1	7/11/1990
Daniel	2	6/24/2004
Anna	1	10/7/2001
Pierre	1	2/22/2009
Ruth	2	6/6/2013
Anthony	1	11/29/1995
Isabella	2	9/28/1997
Jose	2	3/17/2013

firstname	department	startdate
Andrew	1	1/23/1999
Jacob	1	7/11/1990
Anna	1	10/7/2001
Pierre	1	2/22/2009
Anthony	1	11/29/1995

firstname	department	startdate
Daniel	2	6/24/2004
Ruth	2	6/6/2013
Isabella	2	9/28/1997
Jose	2	3/17/2013

ORDER BY startdate

firstname	department	startdate
Jacob	1	7/11/1990
Anthony	1	11/29/1995
Andrew	1	1/23/1999
Anna	1	10/7/2001
Pierre	1	2/22/2009

firstname	department	startdate
Isabella	2	9/28/1997
Daniel	2	6/24/2004
Jose	2	3/17/2013
Ruth	2	6/6/2013

RANK ()

firstname	department	startdate	rank
Jacob	1	7/11/1990	1
Anthony	1	11/29/1995	2
Andrew	1	1/23/1999	3
Anna	1	10/7/2001	4
Pierre	1	2/22/2009	5

firstname	department	startdate	rank
Isabella	2	9/28/1997	1
Daniel	2	6/24/2004	2
Jose	2	3/17/2013	3
Ruth	2	6/6/2013	4

PARTITION BY department

More SQL analytic functions

Example: RANK() function for aggregating over groups of rows

```
SELECT firstname, department, startdate,  
       RANK() OVER ( PARTITION BY department ORDER BY startdate ) AS rank  
FROM Employees;
```

Some other ranking and numbering functions

- CUME_DIST
- DENSE_RANK
- ROW_NUMBER
- PERCENT_RANK

[More SQL numbering functions](#)

Use WITH clauses and subqueries to modularize

```
3 ▾ WITH
4
5   # 2015 filings joined with organization details
6   irs_990_2015_ein AS (
7     SELECT *
8       FROM
9         `bigquery-public-data.irs_990.irs_990_2015`
10      JOIN
11        `bigquery-public-data.irs_990.irs_990_ein` USING (ein)
12      ),
13
14   # duplicate EINs in organization details
15   duplicates AS (
16     SELECT
17       ein AS ein,
18       COUNT(ein) AS ein_count
19       FROM
20         irs_990_2015_ein
21       GROUP BY
22         ein
23       HAVING
24         ein_count > 1
25       )
26
27   # return results to store in a permanent table
28   SELECT
29     irs_990.ein AS ein,
30     irs_990.name AS name,
31     irs_990.noemployeesw3cnt AS num_employees,
32     irs_990.grsrcptspublicuse AS gross_receipts
33   # more fields omitted for brevity
34   FROM irs_990_2015_ein AS irs_990
35   LEFT JOIN duplicates
36   ON
37     irs_990.ein=duplicates.ein
38   WHERE
39   # filter out duplicate records
40     duplicates.ein IS NULL
```

- WITH is simply a named subquery (or Common Table Expression)
- Acts as a temporary table
- Breaks up complex queries
- Chain together multiple subqueries in a single WITH
- You can reference other subqueries in future subqueries

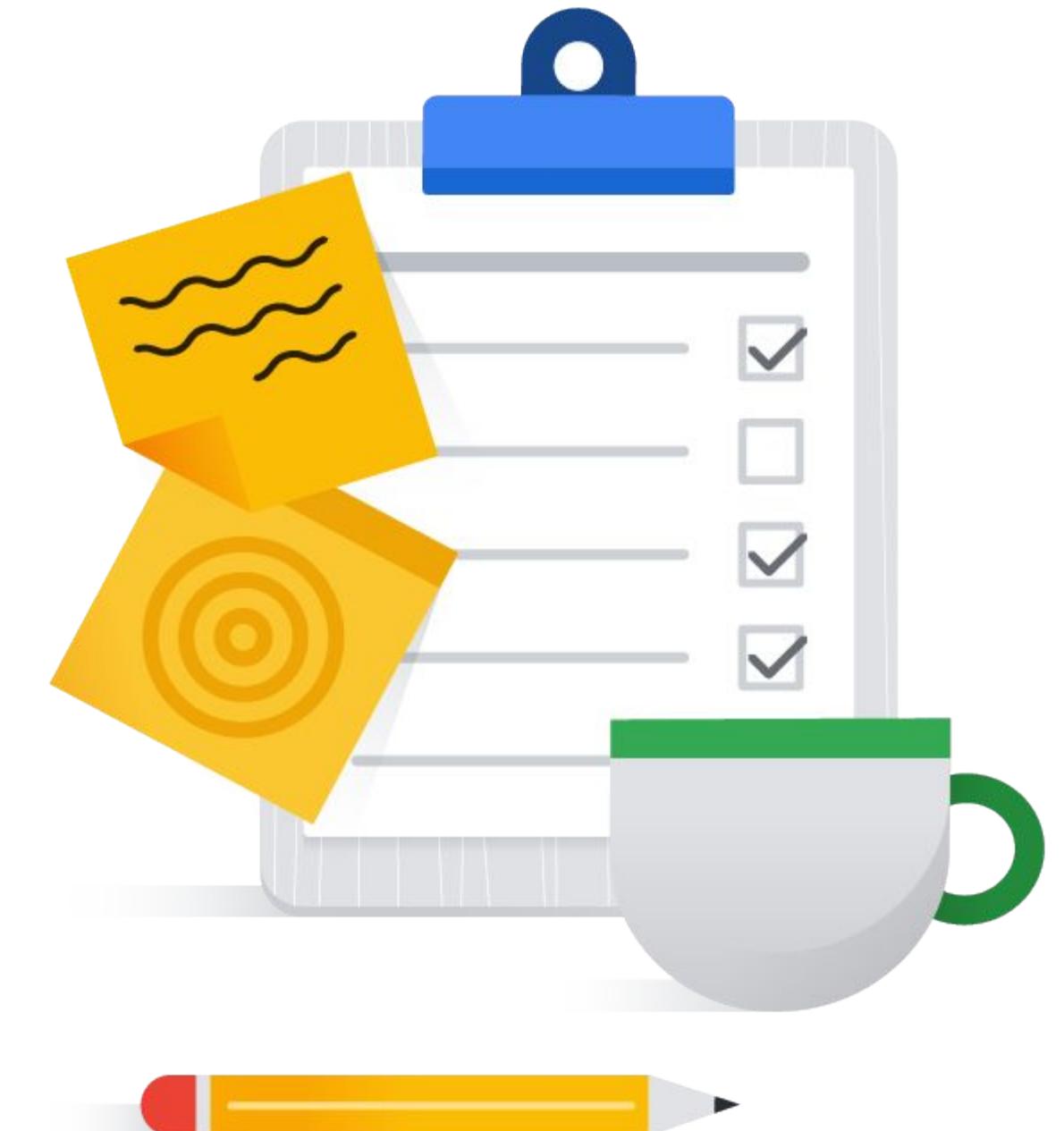
[More SQL query syntax](#)

Advanced BigQuery Functionality and Performance

01 Analytic window functions

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03 Performance considerations



BigQuery has built-in GIS functionality

Example: Can we find the zip codes best served by the New York Citibike system by looking for the number of stations within 1 km of each zip code that have at least 30 bikes?

```

SELECT
  z.zip_code,
  COUNT(*) AS num_stations
FROM
  `bigquery-public-data.new_york_citibike.citibike_stations` AS s,
  `bigquery-public-data.geo_us_boundaries.zip_codes` AS z
WHERE
  ST_DWithin(z.zcta_geom,
    ST_GeogPoint(s.longitude, s.latitude),
    1000) -- 1km
    AND num_bikes_available > 30
GROUP BY
  z.zip_code
ORDER BY
  num_stations DESC

```

Query results SAVE RESULTS ▾ EXPLORE WITH DATA STUDIO

Query complete (1.1 sec elapsed, 128.3 MB processed)

Job information	Results	JSON	Execution details
Row	zip_code	num_stations	
1	10003	21	
2	10002	19	
3	10026	17	
4	10012	16	
5	10029	16	

Use ST_DWITHIN to check if two locations objects are within some distance

- `ST_DWithin(geography_1, geography_2, distance)`

in meters

```
SELECT
    z.zip_code,
    COUNT(*) AS num_stations
FROM
    `bigquery-public-data.new_york_citibike.citibike_stations` AS s,
    `bigquery-public-data.geo_us_boundaries.zip_codes` AS z
WHERE
    ST_DWithin(z.zip_code_geom,
    ST_GeogPoint(s.longitude, s.latitude),
    1000) -- 1km
    AND num_bikes_available > 30
GROUP BY
    z.zip_code
ORDER BY
    num_stations DESC
```

Represent longitude and latitude points as Well Known Text (WKT) using the function `ST_GeogPoint`

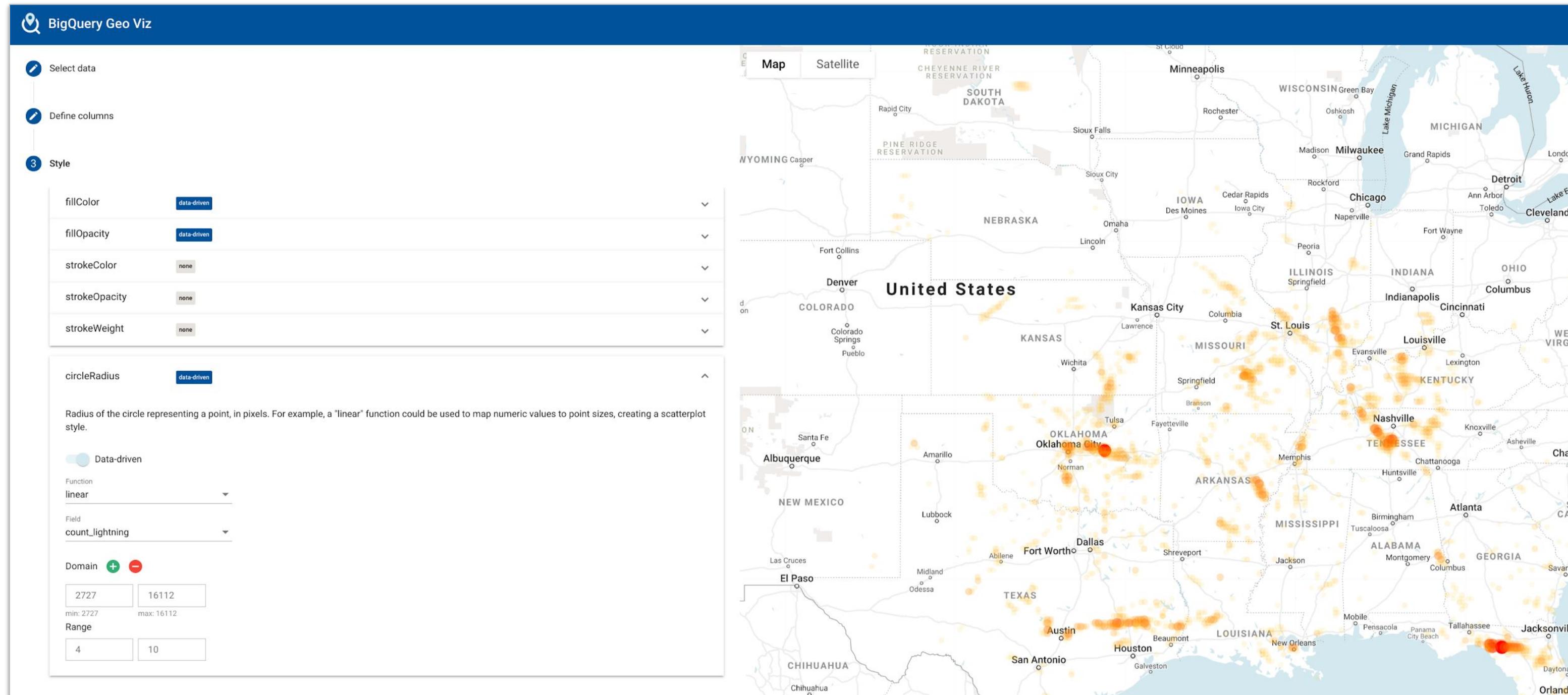
Queries in BigQuery are much more efficient if geographic data is stored as geography types rather than as basics.

If your data is stored in JSON, use **`ST_GeogFromGeoJSON`**

```
SELECT
  z.zip_code,
  COUNT(*) AS num_stations
FROM
  `bigquery-public-data.new_york_citibike.citibike_stations` AS s,
  `bigquery-public-data.geo_us_boundaries.zip_codes` AS z
WHERE
  ST_DWithin(z.zcta_geom,
    ST_GeogPoint(s.longitude, s.latitude),
    1000) -- 1km
  AND num_bikes_available > 30
GROUP BY
  z.zip_code
ORDER BY
  num_stations DESC
```

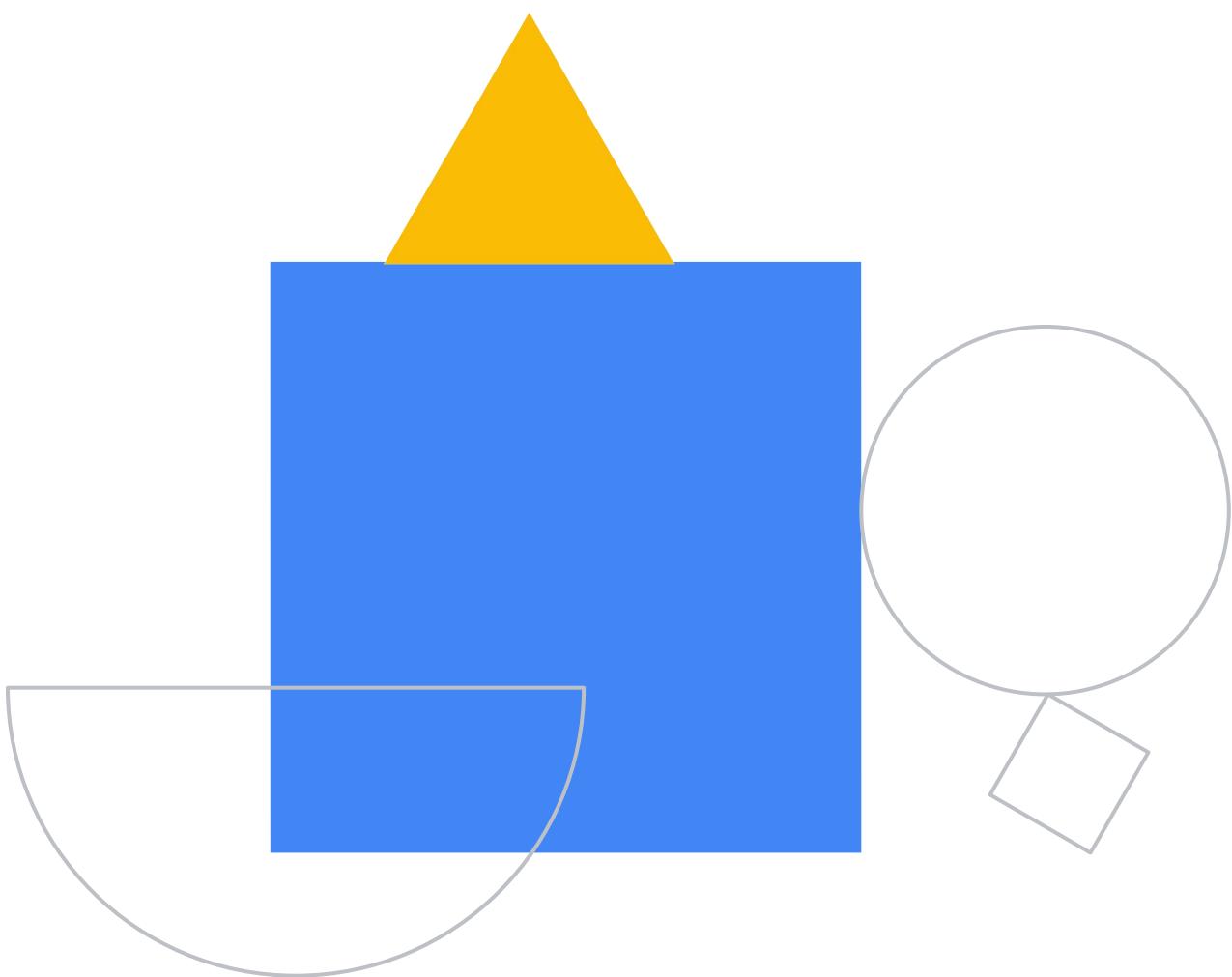
```
SELECT ST_GeogFromGeoJSON(' {"type": "Point", "coordinates": [-73.967416,40.756014]}')
```

Visualization with BigQuery Geo Viz



Demo

Mapping Fastest Growing Zip
Codes with BigQuery GeoViz



Represent points with ST_GeogPoint

- Represented as WKT (Well Known Text)

```
SELECT
  id,
  longitude,
  latitude,
  ST_GeogPoint(longitude, latitude) AS location
FROM
  `bigquery-public-data.london_bicycles.cycle_stations`
LIMIT
  100
```

	id	longitude	latitude	location
	171	-0.186753859	51.4916156	POINT(-0.186753859 51.4916156)
	165	-0.183716959	51.517932	POINT(-0.183716959 51.517932)
	261	-0.191351186	51.5134891	POINT(-0.191351186 51.5134891)
	131	-0.136792671	51.53300545	POINT(-0.136792671 51.53300545)
	467	-0.030556	51.523538	POINT(-0.030556 51.523538)
	43	-0.157183945	51.52026	POINT(-0.157183945 51.52026)
	212	-0.199004026	51.50658458	POINT(-0.199004026 51.50658458)
	517	-0.033085	51.532513	POINT(-0.033085 51.532513)
	704	-0.202802098	51.45682071	POINT(-0.202802098 51.45682071)
	721	-0.026262677	51.53603947	POINT(-0.026262677 51.53603947)

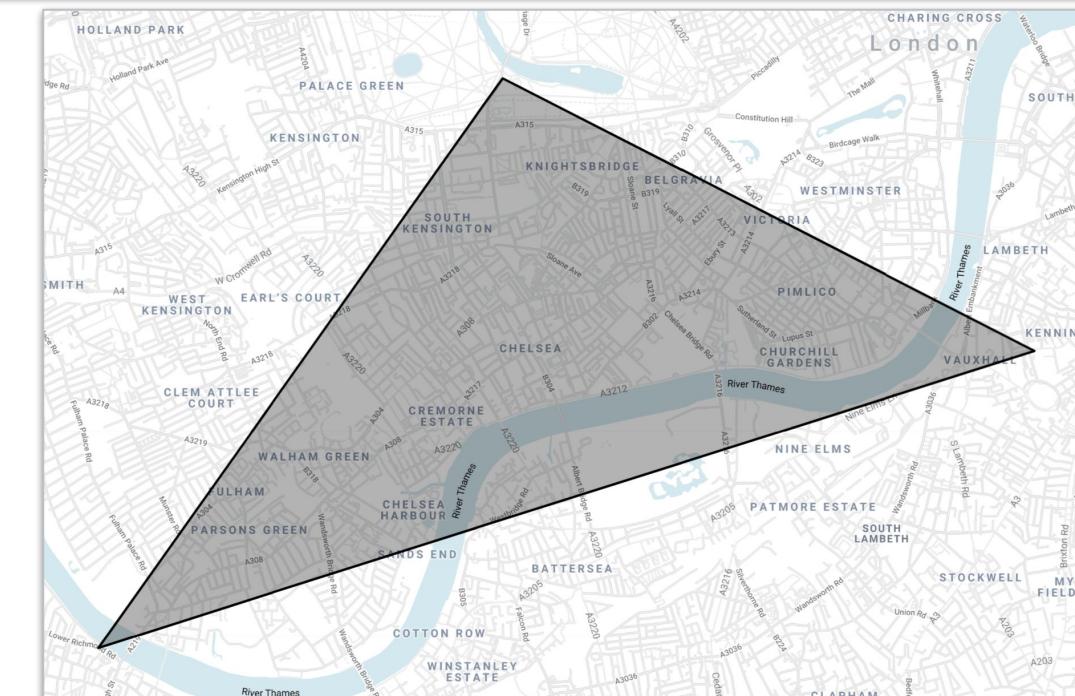
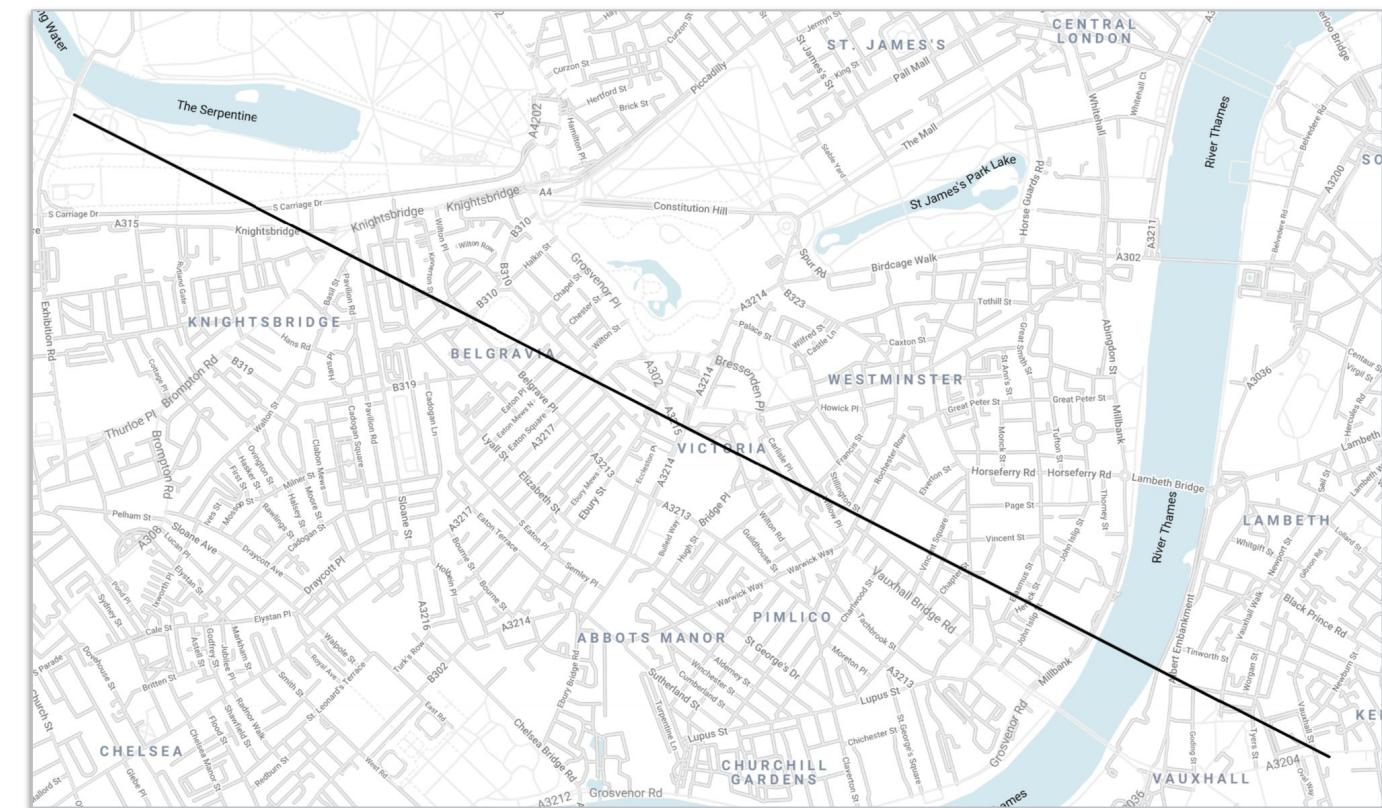


Represent regions with ST_MakeLine and ST_MakePolygon

```

WITH stations AS (
  SELECT ST_GeogPoint(longitude, latitude) FROM `bigquery-public-data.london_bike_stations` AS loc300,
  (SELECT ST_GeogPoint(longitude, latitude) FROM `bigquery-public-data.london_bike_stations` AS loc302,
  (SELECT ST_GeogPoint(longitude, latitude) FROM `bigquery-public-data.london_bike_stations` AS loc305
)
SELECT
  ST_MakeLine([loc300, loc305]) AS seg1,
  ST_MakePolygon(ST_MakeLine([loc300, loc305, loc302])) AS poly
FROM
  stations
  
```

seg1	poly
LINESTRING(-0.17306032 51.505014, -0.115853961 51.48677988)	POLYGON((-0.216573 51.466907, -0.115853961 51.48677988, -0.17306032 ...



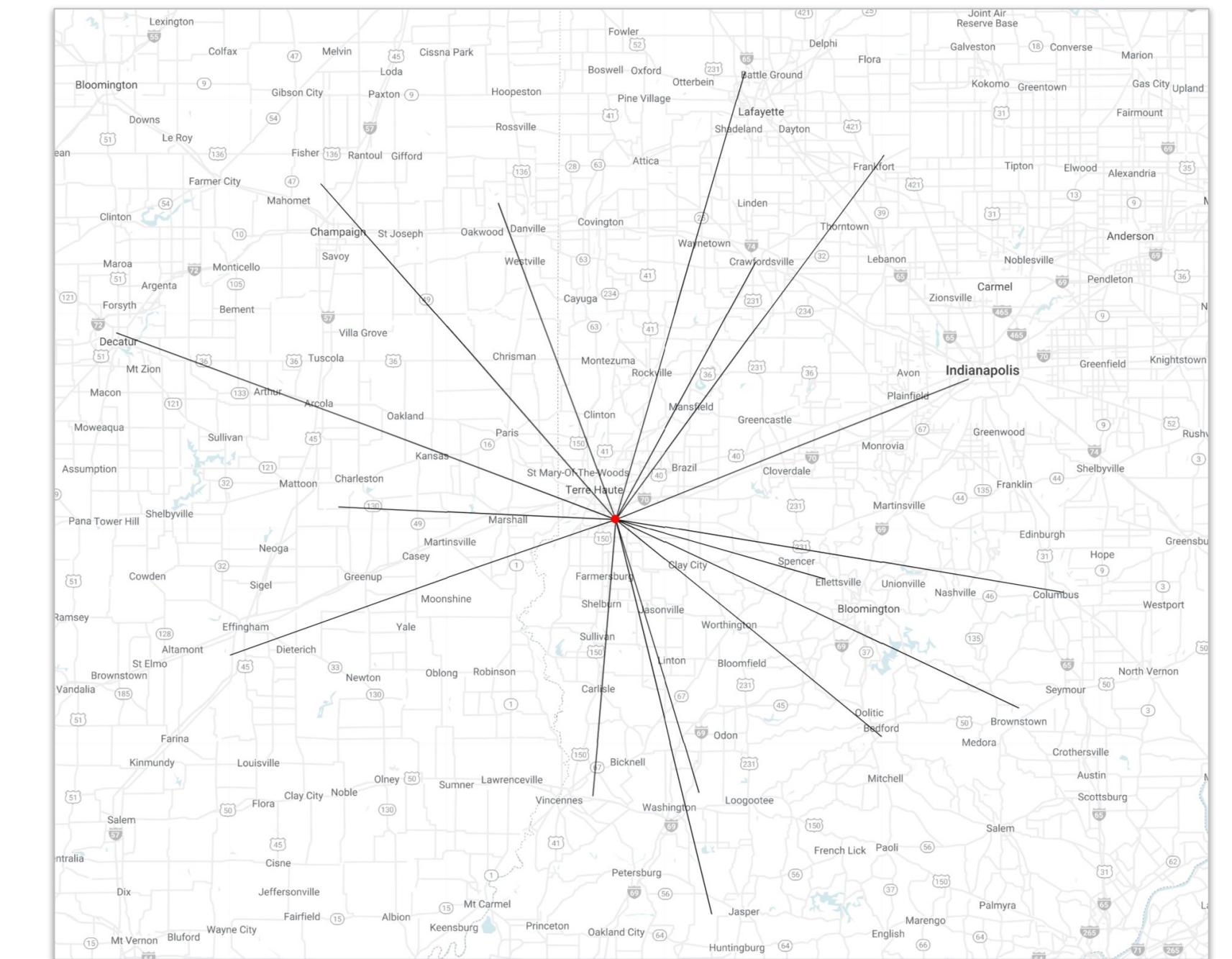
Are locations within some distance?

- **ST_DWithin**

```

SELECT
  m.name AS city,
  m.int_point AS city_coords,
  ST_MakeLine(
    n.int_point,
    m.int_point) AS segs
FROM
  `bigquery-public-data.geo_us_boundaries.us_msa` AS n,
  `bigquery-public-data.geo_us_boundaries.us_msa` AS m
WHERE
  n.name='Terre Haute, IN'
  AND ST_DWithin(
    n.int_point,
    m.int_point,
    1.5e5) --150km
  
```

city	city_coords	segs
Crawfordsville, IN	POINT(-86.8927145 40.0402962)	LINESTRING(-87.3470958 39.392389, -86.892714...
Decatur, IL	POINT(-88.9615288 39.8602372)	LINESTRING(-87.3470958 39.392389, -88.961528...
Washington, IN	POINT(-87.076944 38.696089)	LINESTRING(-87.3470958 39.392389, -87.076944 ...
Indianapolis-Carmel-Anderson, IN	POINT(-86.2045408 39.7449323)	LINESTRING(-87.3470958 39.392389, -86.204540...
Lafayette-West Lafayette, IN	POINT(-86.9304747 40.5147171)	LINESTRING(-87.3470958 39.392389, -86.930474...
Bloomington, IN	POINT(-86.6717544 39.2417362)	LINESTRING(-87.3470958 39.392389, -86.671754...
Seymour, IN	POINT(-86.0425161 38.9119571)	LINESTRING(-87.3470958 39.392389, -86.042516...
Frankfort, IN	POINT(-86.4775665 40.305944)	LINESTRING(-87.3470958 39.392389, -86.477566...



Other predicate functions

- Do locations intersect?
 - **ST_Intersects**
- Is one geometry contained inside another?
 - **ST_Contains**
- Does a geography engulf another?
 - **ST_CoveredBy**

```
WITH geos AS (
  SELECT
    (SELECT state_geom FROM `bigquery-public-data.geo_us_boundaries.us_states`  

     WHERE state_name='Massachusetts') AS ma_poly,  

    (SELECT msa_geom FROM `bigquery-public-data.geo_us_boundaries.us_msa`  

     WHERE name='Boston-Cambridge-Newton, MA-NH') AS boston_poly,  

    (SELECT msa_geom FROM `bigquery-public-data.geo_us_boundaries.us_msa`  

     WHERE name='Seattle-Tacoma-Bellevue, WA') AS seattle_poly
)
SELECT
  ST_Intersects(boston_poly, ma_poly) boston_in_ma,
  ST_Intersects(seattle_poly, ma_poly) seattle_in_ma
FROM
  geos
```

boston_in_ma	seattle_in_ma
true	false

Advanced BigQuery Functionality and Performance

01

Analytic window functions

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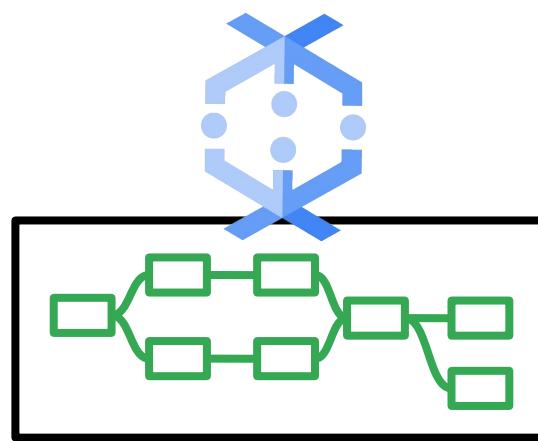
GIS functions

03

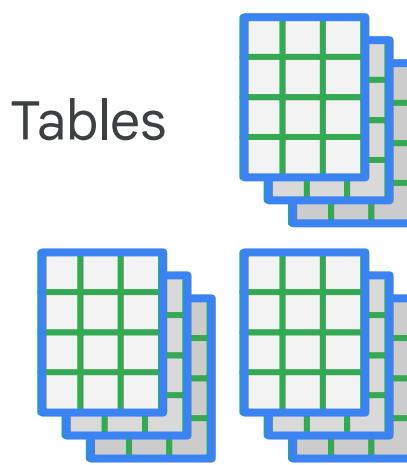
Performance considerations



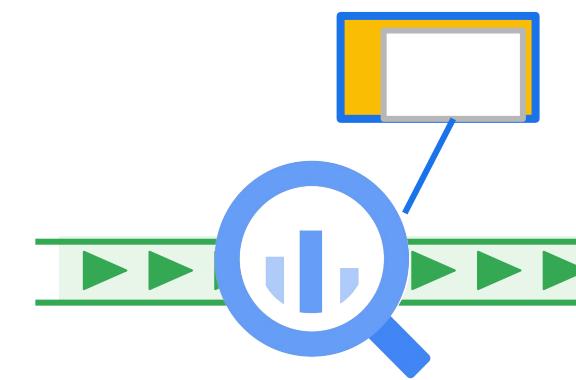
Best practices for fast, smart, data-driven decisions



Use Dataflow to do the processing and data transformations

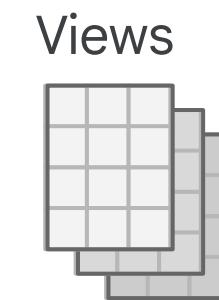


Create multiple tables for easy analysis



Use BigQuery for streaming analysis and dashboards

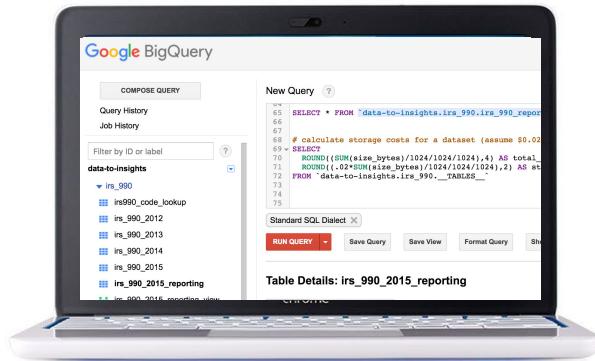
Store data in BigQuery for low cost long term storage



Create views for common queries

Best practices for analyzing data with BigQuery

Dataset



Know your data

Questions

Give me a list of all organizations sorted by the revenue lowest to highest

Ask good questions

SQL

```
SELECT  
    name,  
    revenue  
FROM dataset  
ORDER BY revenue;
```

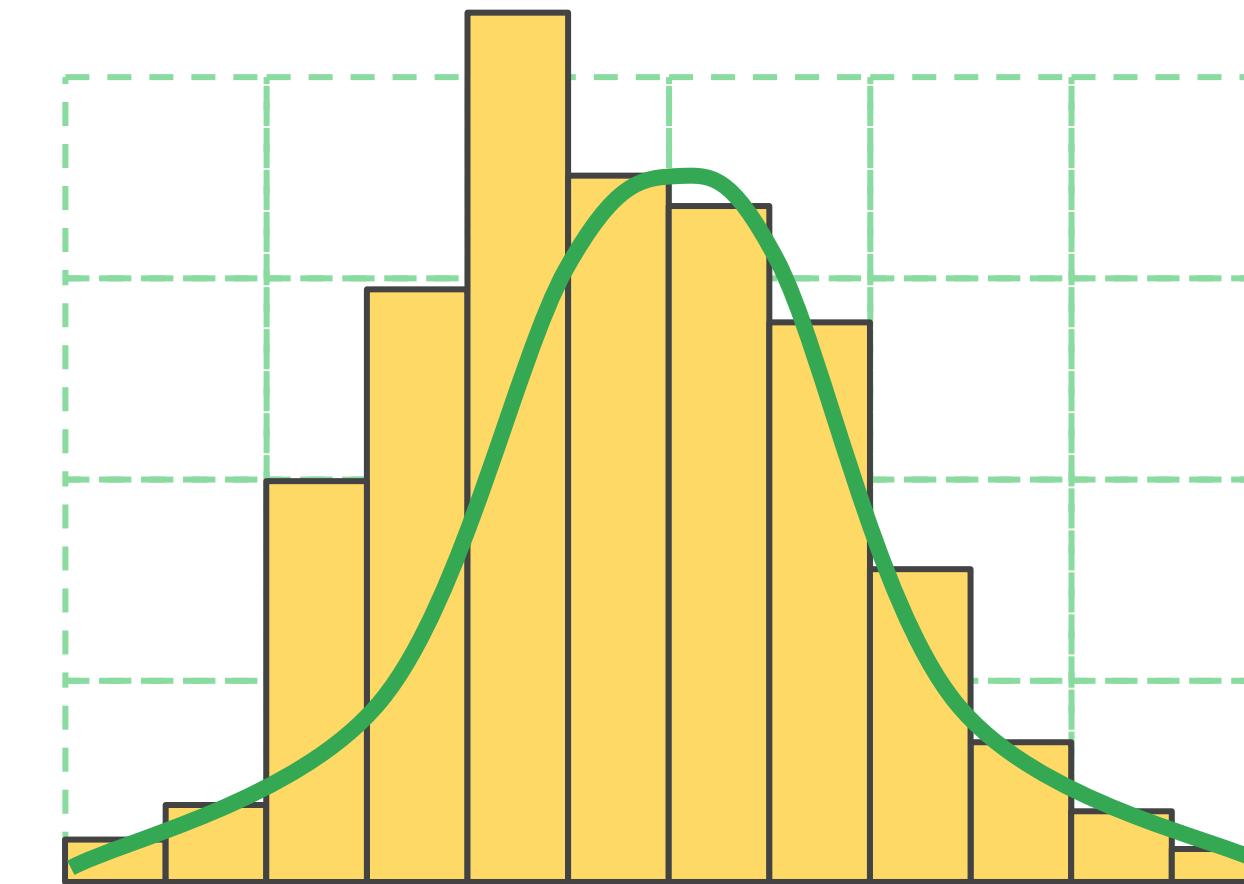
Use queries effectively

How to optimize in production? Revisit the schema.

Revisit the data.

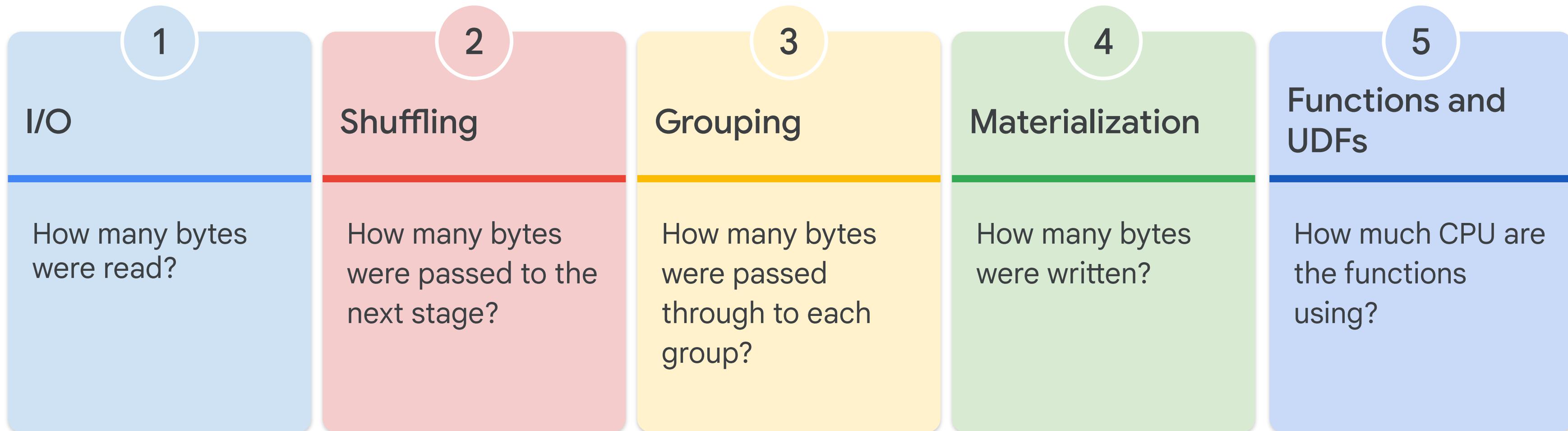
Customer	Street Number	Street Name	City	Country	Phone Number

Customer	Address	Phone Number



Stop accumulating work that could be done earlier.

Improve scalability by improving efficiency



Less work = Faster query

Optimize BigQuery queries

`SELECT *`

Avoid using unnecessary columns

`WHERE`

Filter early and often

`JOIN`

Put the largest table on the left

`GROUP BY`

Low cardinality is faster than high cardinality

`APPROX_COUNT_DISTINCT`

Some built-in functions are faster than others, and all are faster than JavaScript UDFs.

Is faster than

`COUNT(DISTINCT)`

`ORDER`

On the outermost query

*

Use wildcards to query multiple tables

`--time_partitioning_type`

Time partitioning tables for easier search

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
```

Partitioning can improve query cost and performance by cutting down on 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  
...
```

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

c1	c2	c3	eventDate	c5
			2019-01-01	
			2019-01-02	
			2019-01-03	
			2019-01-04	
			2019-01-05	

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

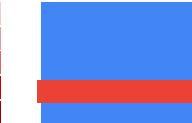
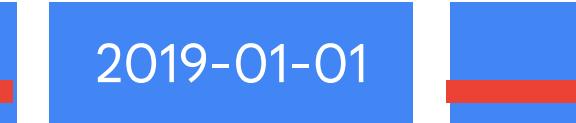
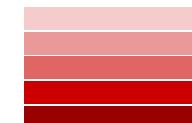
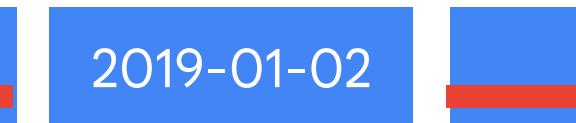
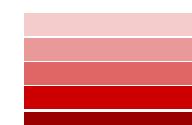
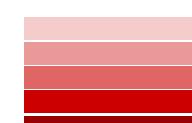
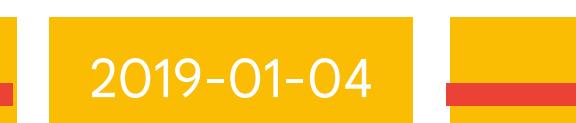
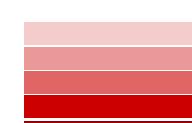
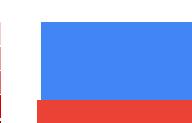
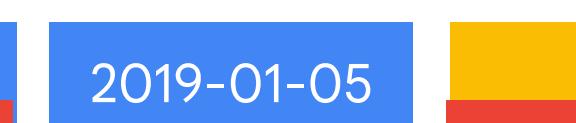
Partitioned tables

c1	userId	c3	eventDate	c5
			2019-01-01	
			2019-01-02	
			2019-01-03	
			2019-01-04	
			2019-01-05	

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

Clustered tables

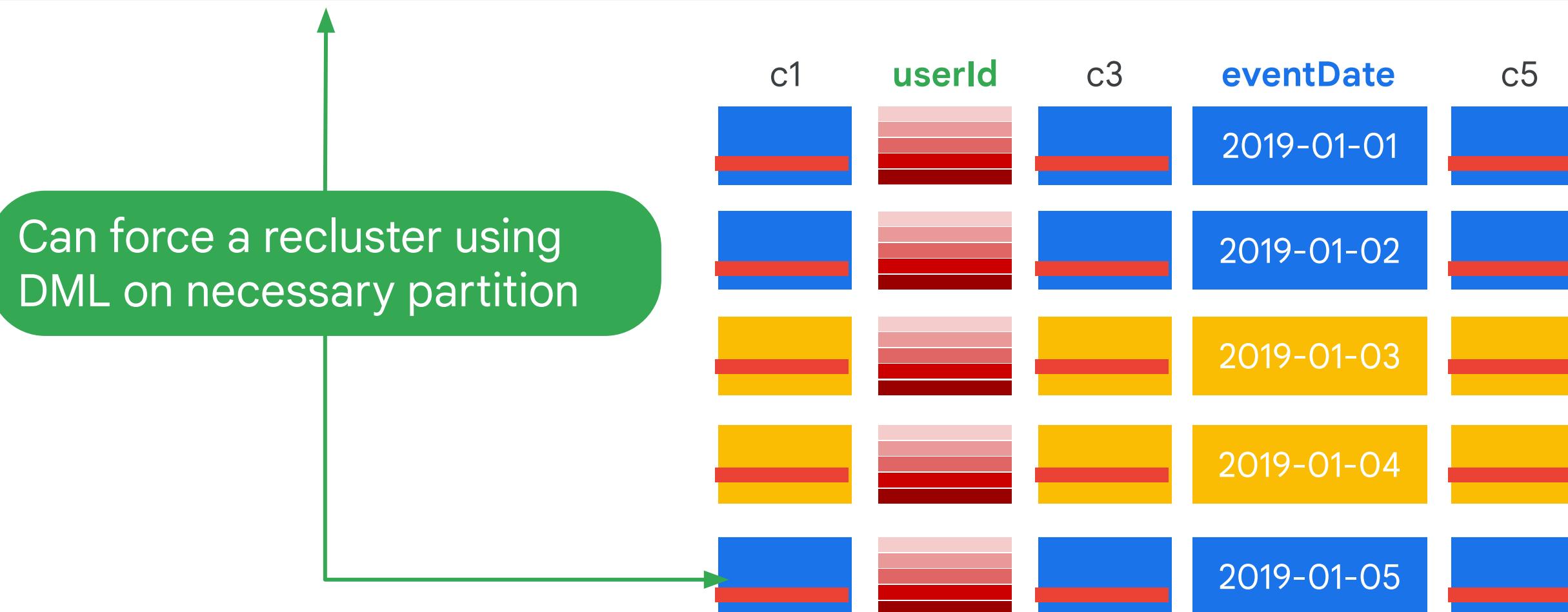
Set up clustering at table creation time

c1	userId	c3	eventDate	c5
			2019-01-01	
			2019-01-02	
			2019-01-03	
			2019-01-04	
			2019-01-05	

```
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
```

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)
```



BigQuery will automatically recluster your data

Automatic re-clustering

free

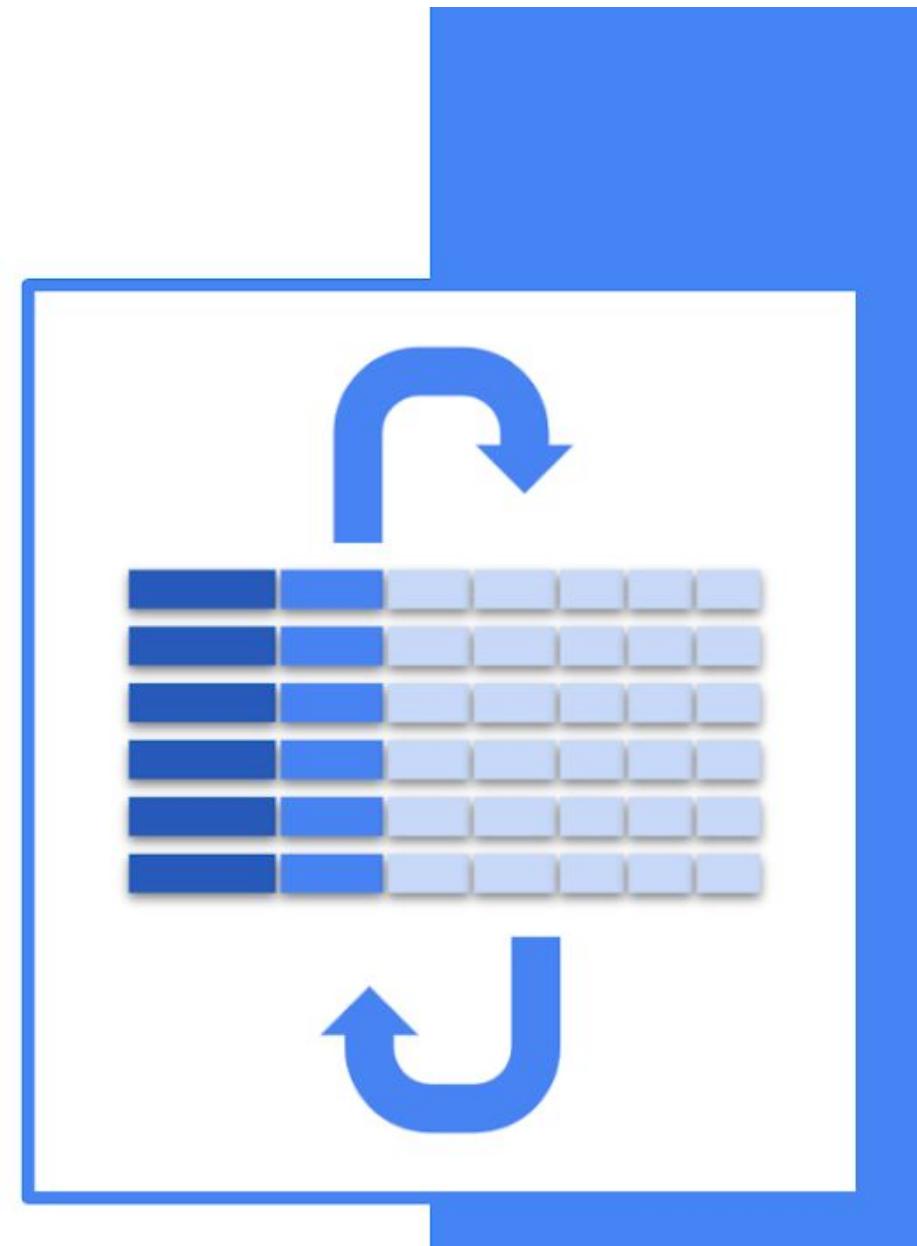
Doesn't consume your query resources

maintenance-free

Requires no setup or maintenance

autonomous

Automatically happens in the background



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.

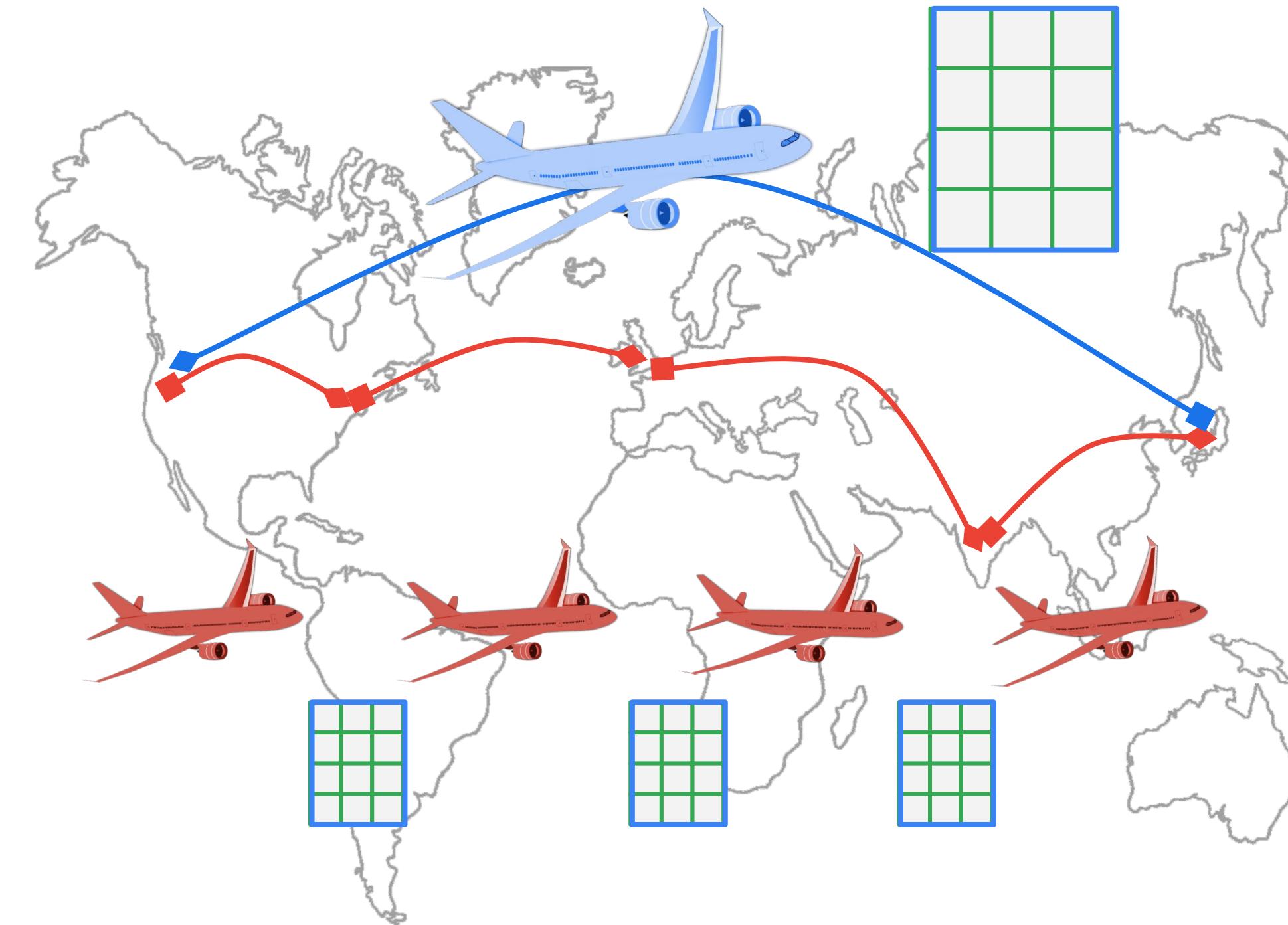
Prioritized clustering of up to 4 columns, on more diverse types (but no nested columns).

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.

Break queries into stages using intermediate tables

Read only what is needed and store results at each step.



Track input and output counts with Execution details tab

Query complete (27.0 sec elapsed, 289.4 GB processed)						
Job information	Results	JSON	Execution details			
<p>For help debugging or optimizing your query, check our documentation. Learn more</p>						
Elapsed time	Slot time consumed <small>?</small>	Bytes shuffled <small>?</small>	Bytes spilled to disk <small>?</small>			
27.0 sec	10 hr 35 min	382.37 GB	0 B <small>i</small>			
Worker timing <small>?</small>						
Stages	Wait	Read	Compute	Write	Rows	
S00: Input <small>▼</small>	Avg: 52 ms	41 ms	3455 ms	25 ms	Input:	9,100,000
	Max: 127 ms	50 ms	3790 ms	44 ms	Output:	9,100,000
S01: Input <small>▼</small>	Avg: 8 ms	16 ms	51 ms	11 ms	Input:	48,000
	Max: 8 ms	16 ms	51 ms	11 ms	Output:	48,000
S02: Input <small>▼</small>	Avg: 1 ms	15 ms	106 ms	10 ms	Input:	86,400
	Max: 1 ms	15 ms	106 ms	10 ms	Output:	86,400
S03: Input <small>▼</small>	Avg: 26 ms	21 ms	35 ms	8 ms	Input:	73,049
	Max: 26 ms	21 ms	35 ms	8 ms	Output:	36,526

Using BigQuery plans to optimize

Significant difference between avg and max time?

Probably data skew



- Check with APPROX_TOP_COUNT
- Filter early as a workaround

Most time spent reading during intermediate stages?

Order of operations?



- Consider filtering earlier in the query

Most time spent on CPU tasks?

Probably slow code



- Look carefully at UDFs
- Use approximate functions
- Filter earlier in the query

Analyze BigQuery performance in Cloud Monitoring

Custom Dashboards

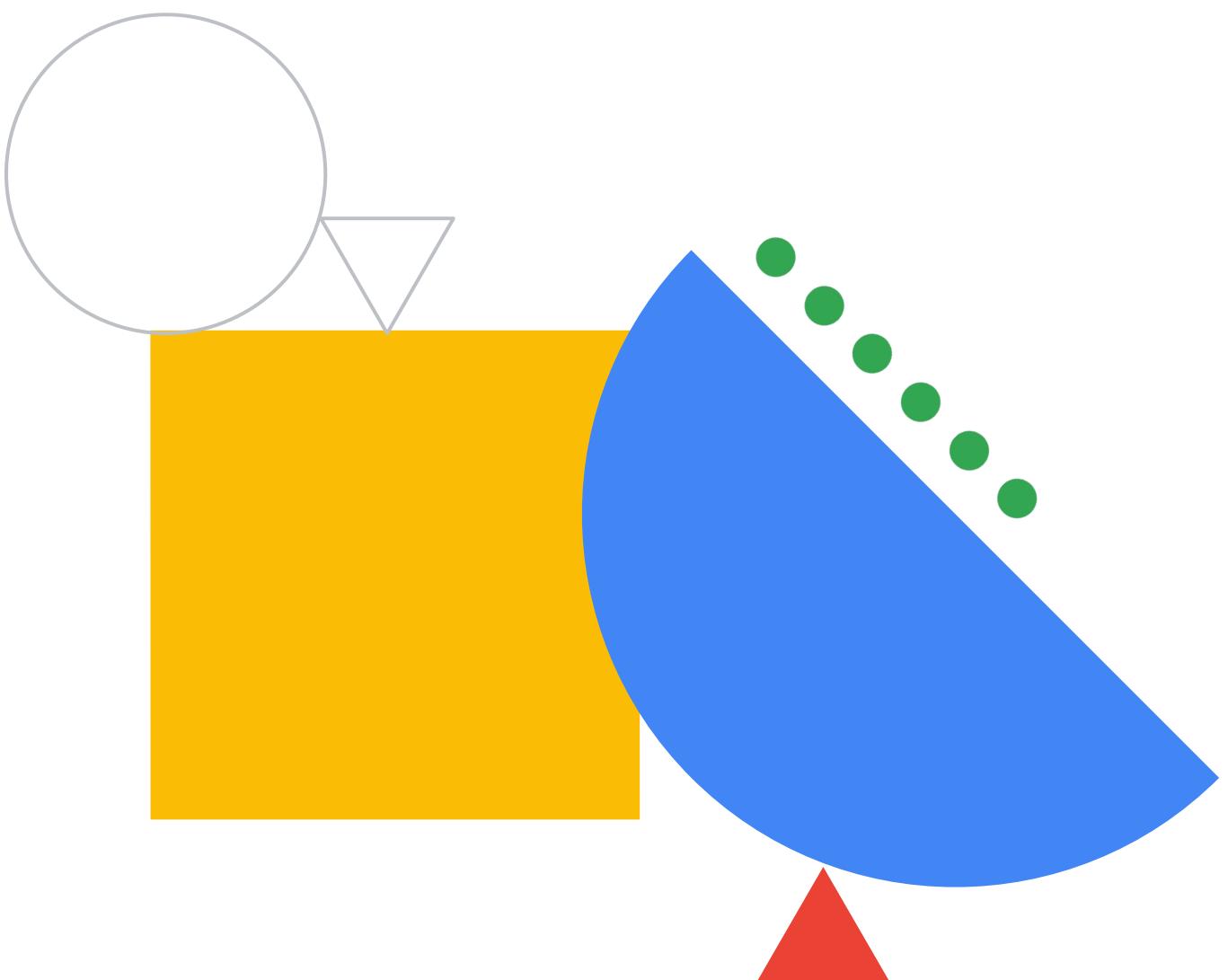
Metrics include:

- slots utilization
- queries in flight
- upload bytes
- stored bytes



Lab Intro

Optimizing your BigQuery
Queries for Performance



Lab objectives

- 01 Minimizing I/O
- 02 Caching results of previous queries
- 03 Performing efficient joins
- 04 Avoid overwhelming single workers
- 05 Using approximate aggregation functions



Once your data is loaded into BigQuery, you are charged for storing it

Active Storage Pricing

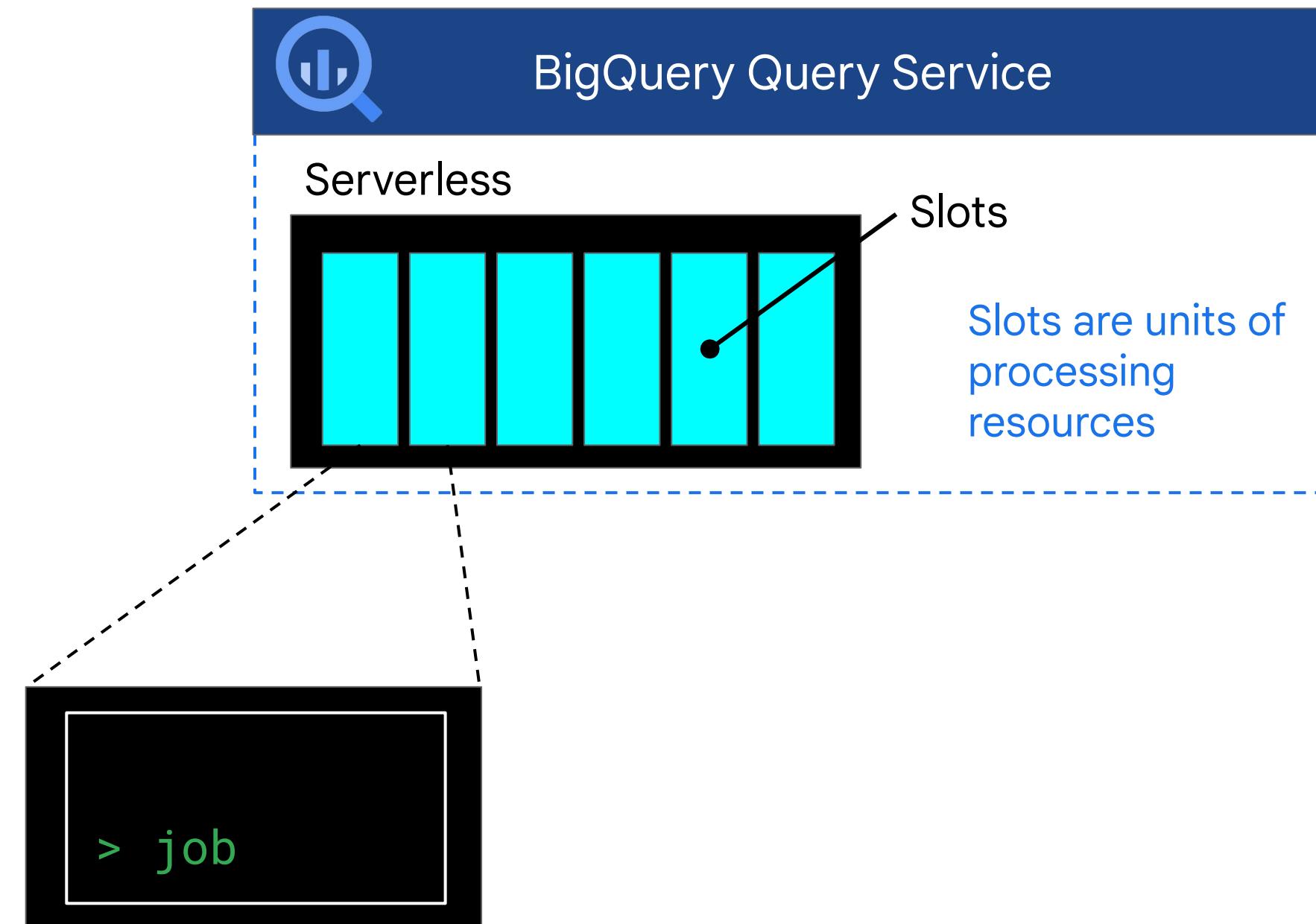
Storage pricing is prorated per MB, per second.
For example, if you store:

- 100 MB for half a month, you pay \$0.001
(a tenth of a cent)
- 500 GB for half a month, you pay \$5
(\$0.02/GB per month)
- 1 TB for a full month, you pay \$20

Long-term Storage Pricing

- Table or partition not edited 90+ consecutive days
- Pricing drops \approx 50%
- No degradation (performance, durability, availability, functionality)
- Applies to BigQuery storage only

Slots are units of resources that are consumed when a query is run



Which BigQuery pricing model to pick?

On-Demand Pricing

- \$5/TB of data processed
- Quota limit of 2,000 slots
- Slots shared amongst all on demand users
- 1st TB of data processed is free each month

Good for **exploratory work** and discovery

Flat-Rate Pricing

- Fixed rate pricing is \$10k* per 500 slots per month
- Slots are dedicated 24/7
- Starting at 500 slots
- Unlimited use of slots

Good for **multiple large workloads** and **consistent monthly billing**

Flex Slots provide flexibility and control

-  Deploy BigQuery Slots in minutes
-  Only pay for what you consume
-  Cancel any time after 60 seconds
-  Combine with longer-term commitments

Flex Slots enable you to scale

- Planning for major calendar events, such as the tax season, Black Friday, popular media events, and video game launches.
- Meeting cyclical periods of high demand for analytics, like Monday mornings.
- Completing data warehouse evaluations and dialing in the optimal number of slots to use.

Considerations when enrolling for flat-rate pricing

- Flex slots are a special commitment type and a subject to capacity availability.
- Monthly commitments cannot be canceled or downgraded for 30 calendar days from the purchase confirmation date.
- Annual commitments cannot be canceled or downgraded for one calendar year.
- To purchase additional BigQuery slots, you must enter into a new commitment.
- Flat-rate pricing is purchased for a specific BigQuery location.
- Flat-rate and on-demand pricing can be used together.
- To discontinue a flat-rate pricing plan, you must cancel or downgrade your commitment.

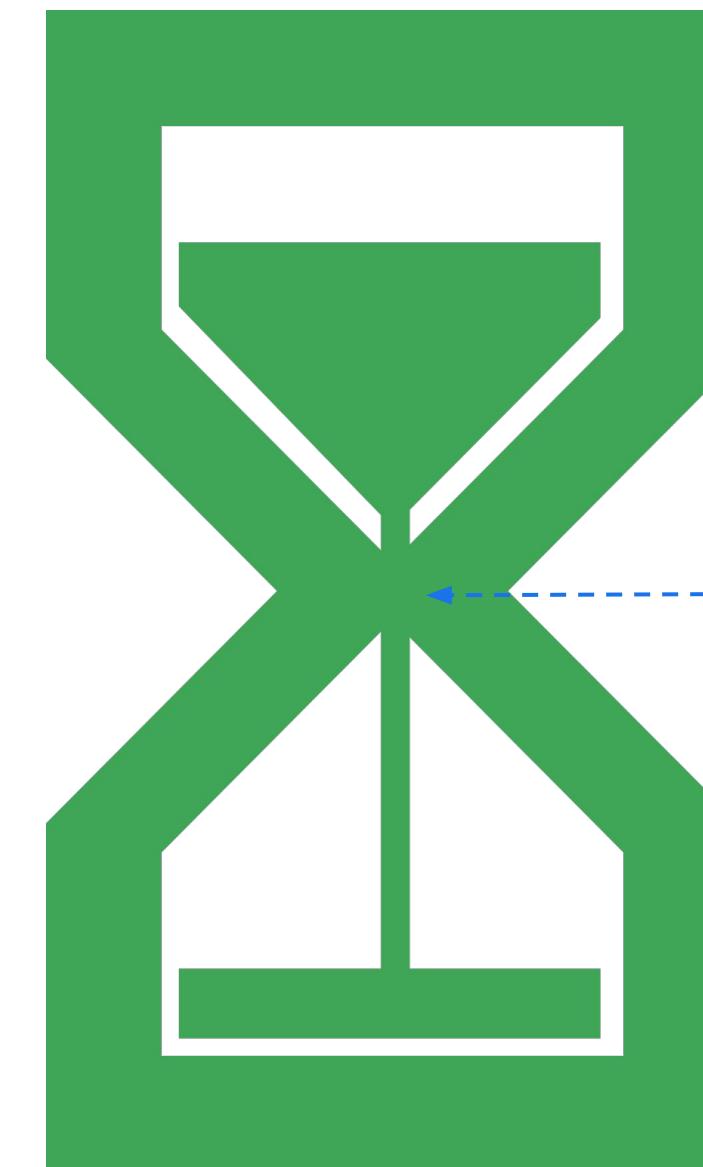
Estimating the right BigQuery slots allocation is critical

Guideline:

It is recommended to plan for 2,000 BigQuery slots for every 50 medium-complexity queries simultaneously

50 queries = 2,000 slots

(quota: 100 concurrent queries, but this can be raised)

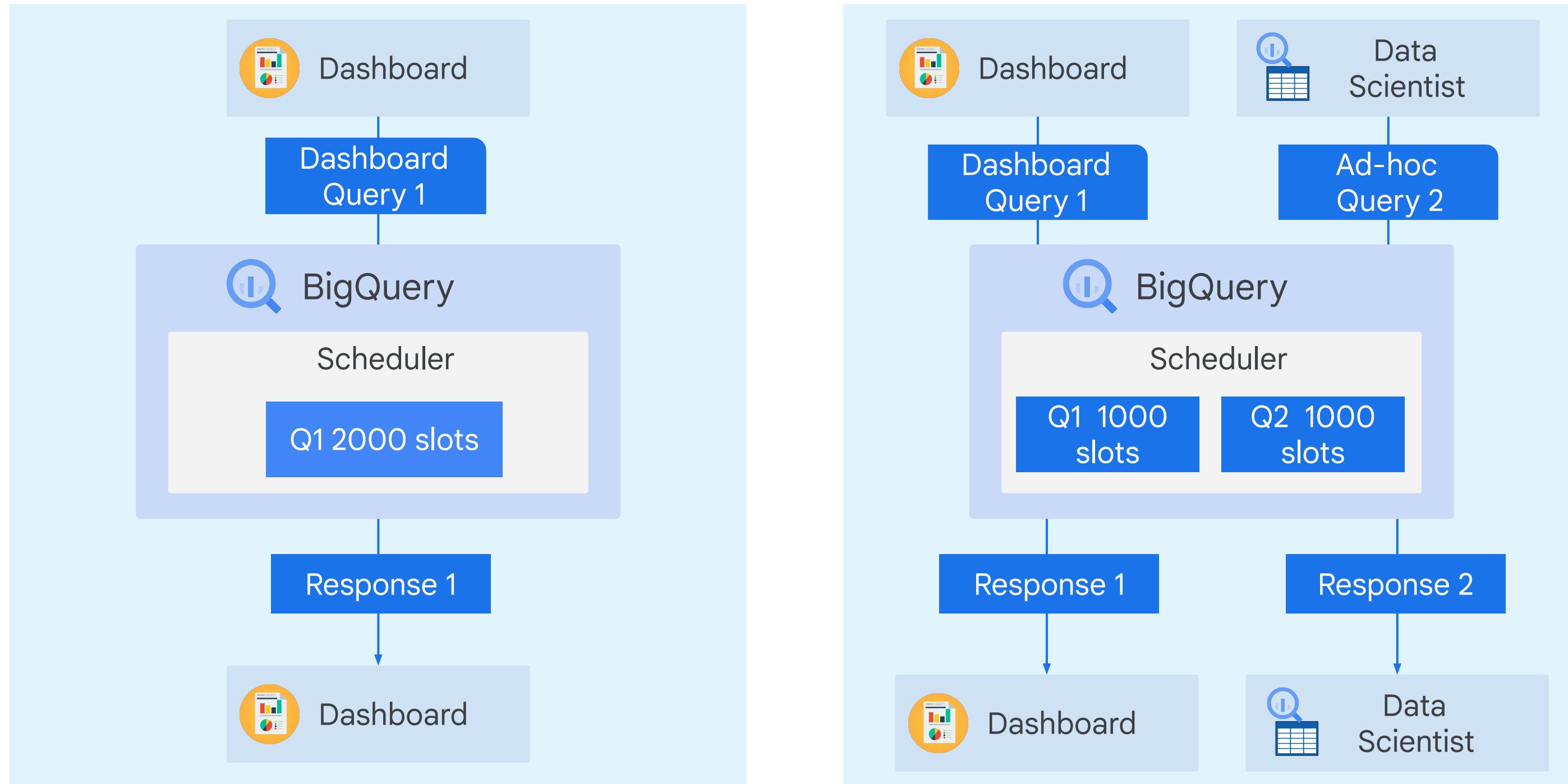


Slots available

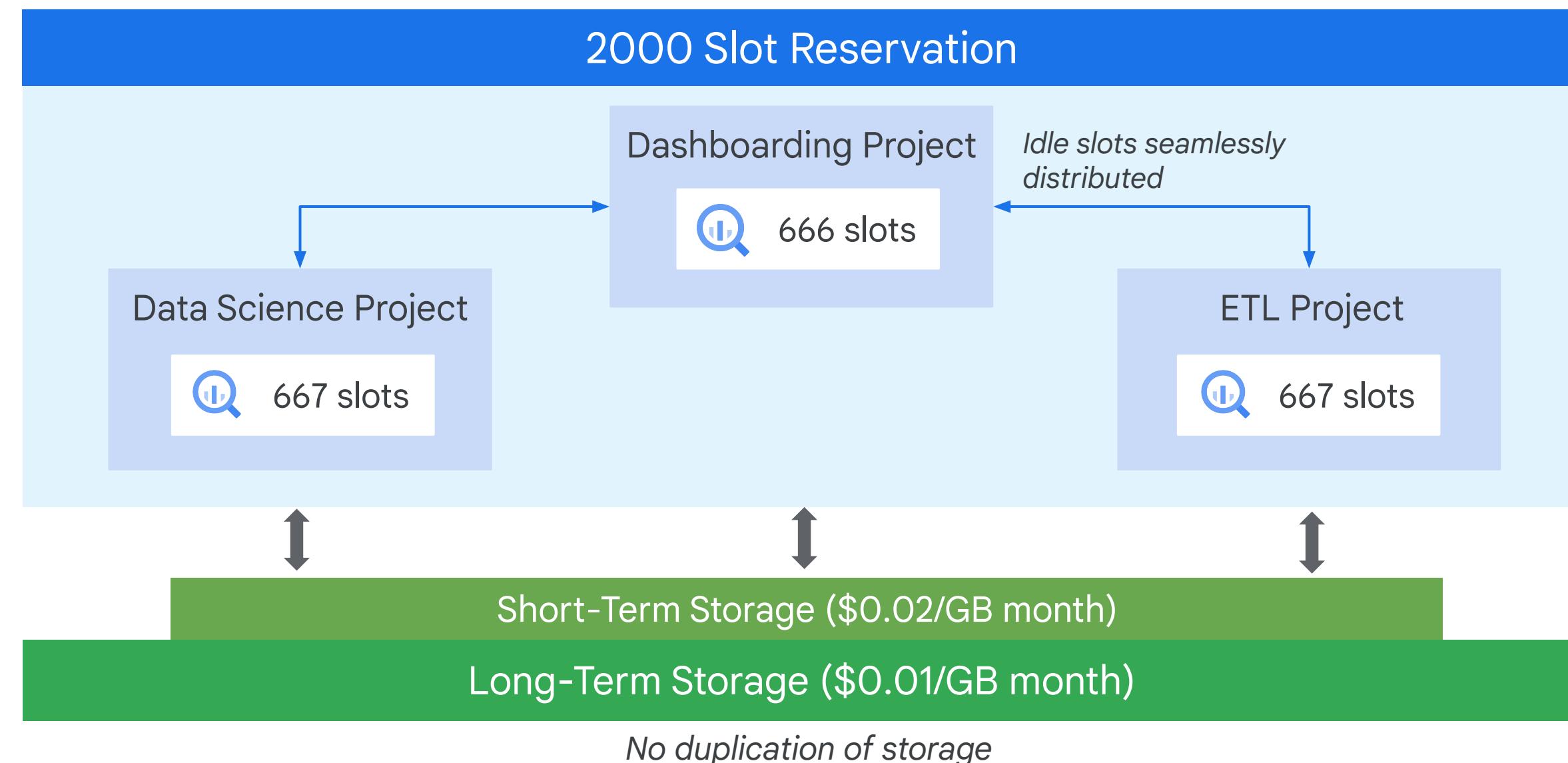
More slots = Faster depletion rate

More concurrent queries = Slower depletion rate

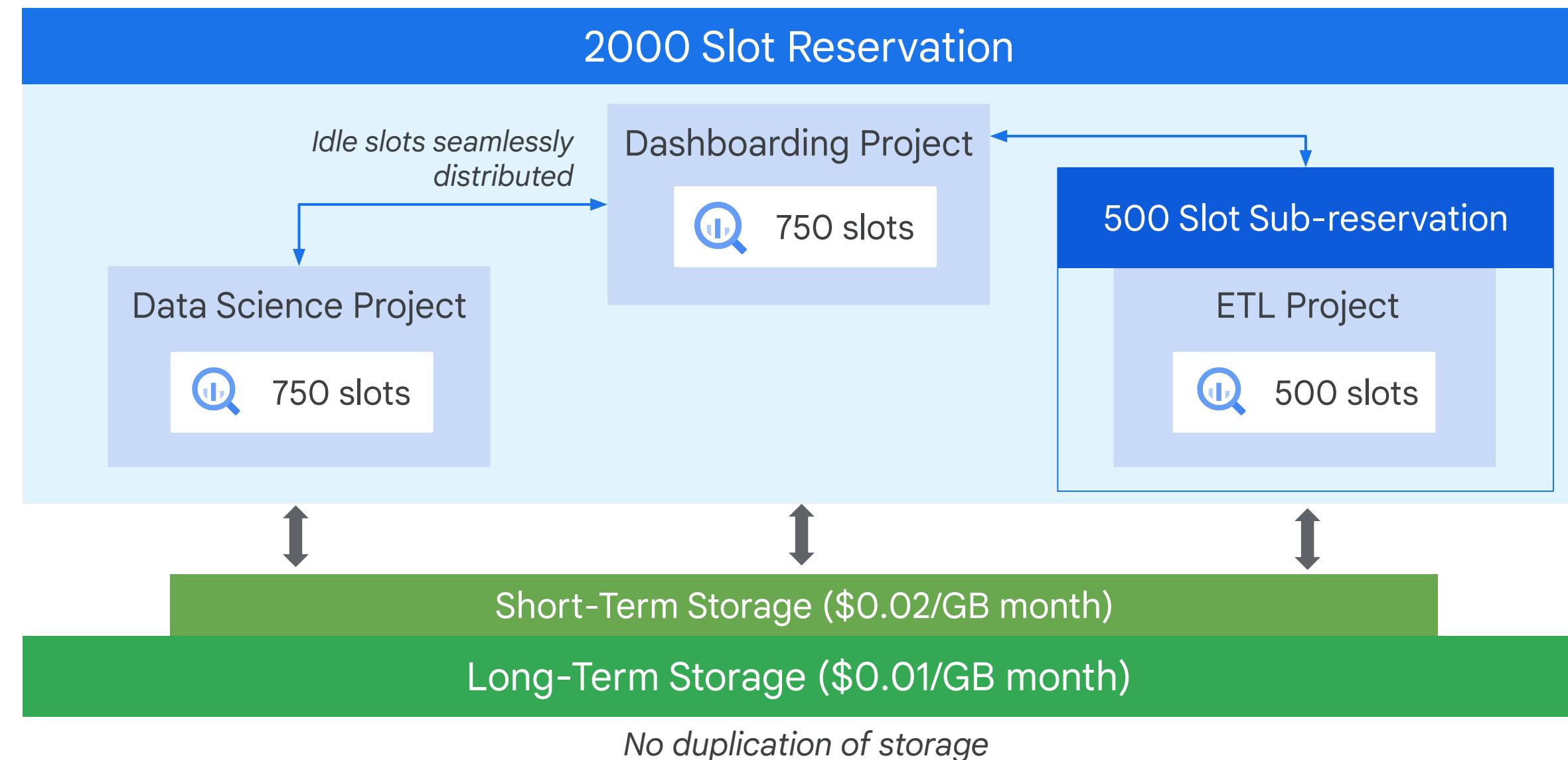
BigQuery has a fair scheduler



Concurrency is fair across projects, users, and queries, with unused capacity fairly divided among existing tasks

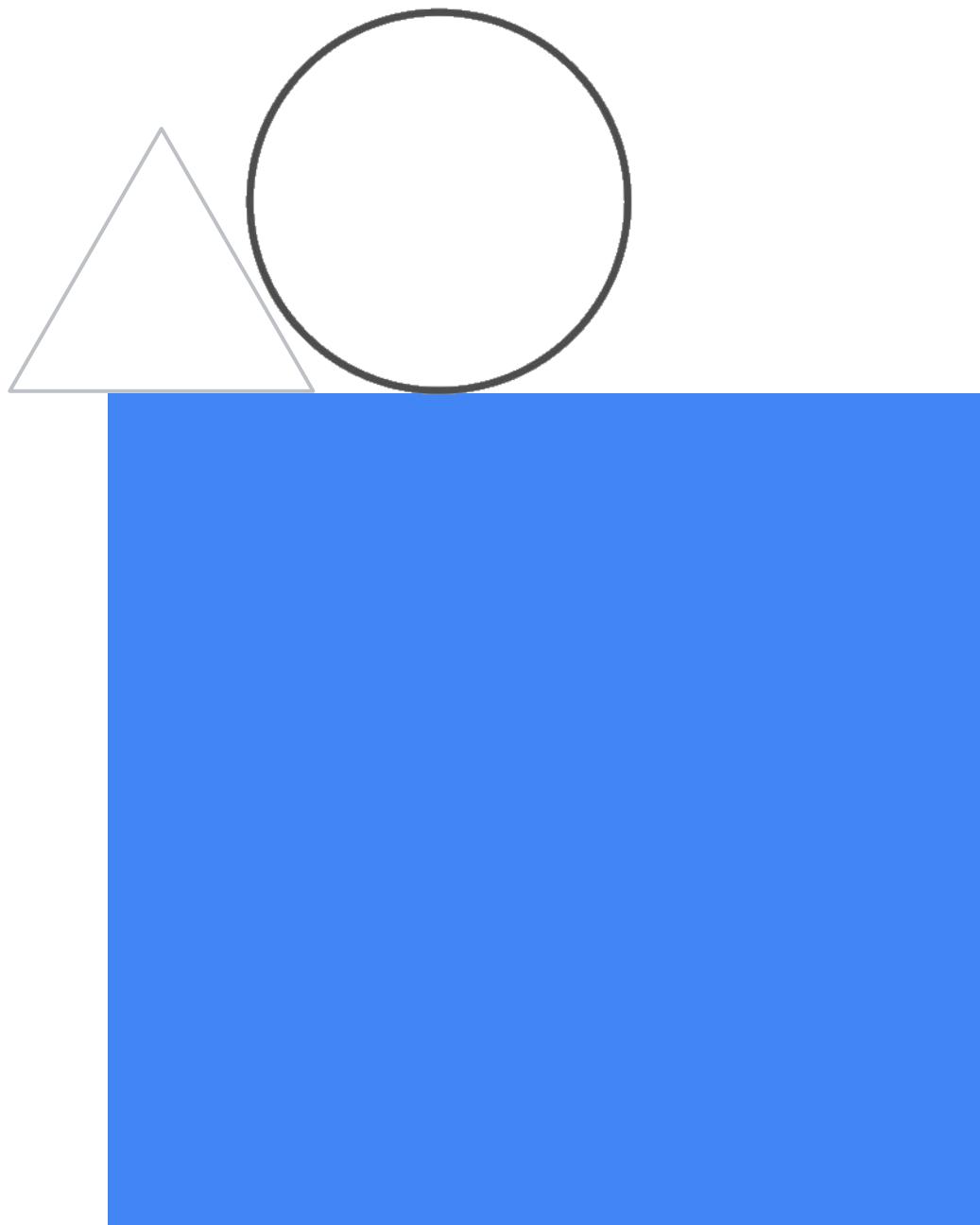


To prioritize projects, set up a hierarchical reservation



Lab Intro

Partitioned Tables in BigQuery



Lab objectives

01

Query partitioned datasets

02

Create your own dataset partitions to improve query performance and reduce cost



