Predict Taxi Fare with a BigQuery ML Forecasting Model

1 hour No cost

GSP246

Google Cloud Self-Paced Labs

Overview

BigQuery is Google's fully managed, NoOps, low cost analytics database. With BigQuery you can query terabytes and terabytes of data without having any infrastructure to manage, or needing a database administrator.

BigQuery ML provides data analysts the ability to create, train, evaluate, and predict with machine learning models with minimal coding.

In this lab, you work with millions of New York City yellow taxi cab trips available in a BigQuery Public Dataset. You use this data to create a machine learning model inside of BigQuery to predict the fare of the cab ride given your model inputs and evaluate the performance of your model and make predictions with it.

What you'll learn

In this lab, you learn to perform the following tasks:

- Use BigQuery to find public datasets
- Query and explore the public taxi cab dataset
- Create a training and evaluation dataset to be used for batch prediction
- Create a forecasting (linear regression) model in BigQuery ML
- Evaluate the performance of your machine learning model

Setup and requirements

Before you click the Start Lab button

Read these instructions. Labs are timed and you cannot pause them. The timer, which starts when you click **Start Lab**, shows how long Google Cloud resources will be made available to you.

This hands-on lab lets you do the lab activities yourself in a real cloud environment, not in a simulation or demo environment. It does so by giving you new, temporary credentials that you use to sign in and access Google Cloud for the duration of the lab.

To complete this lab, you need:

- Access to a standard internet browser (Chrome browser recommended).

> **Note:** Use an Incognito or private browser window to run this lab. This prevents any conflicts between your personal account and the Student account, which may cause extra charges incurred to your personal account.

- Time to complete the lab---remember, once you start, you cannot pause a lab.

> **Note:** If you already have your own personal Google Cloud account or project, do not use it for this lab to avoid extra charges to your account.

How to start your lab and sign in to the Google Cloud console

1. Click the **Start Lab** button. If you need to pay for the lab, a pop-up opens for you to select your payment method. On the left is the **Lab Details** panel with the following:

    - The **Open Google Cloud console** button
    - Time remaining
    - The temporary credentials that you must use for this lab
    - Other information, if needed, to step through this lab

2. Click **Open Google Cloud console** (or right-click and select **Open Link in Incognito Window** if you are running the Chrome browser).

    The lab spins up resources, and then opens another tab that shows the **Sign in** page.

    Tip: Arrange the tabs in separate windows, side-by-side.

    > **Note:** If you see the **Choose an account** dialog, click **Use Another Account**.

3. If necessary, copy the **Username** below and paste it into the **Sign in** dialog.

    ```
    student-01-c5a503570e33@qwiklabs.net
    ```

    You can also find the **Username** in the **Lab Details** panel.

4. Click **Next**.

5. Copy the **Password** below and paste it into the **Welcome** dialog.

```
b9r3OENziLIS
```

content_c

You can also find the **Password** in the **Lab Details** panel.

6. Click **Next**.

Important: You must use the credentials the lab provides you. Do not use your Google Cloud account credentials.

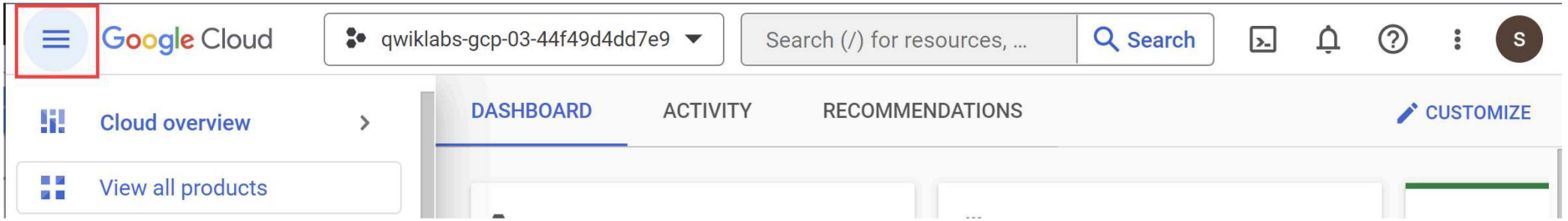
Note: Using your own Google Cloud account for this lab may incur extra charges.

7. Click through the subsequent pages:

   - Accept the terms and conditions.
   - Do not add recovery options or two-factor authentication (because this is a temporary account).
   - Do not sign up for free trials.

After a few moments, the Google Cloud console opens in this tab.

Note: To view a menu with a list of Google Cloud products and services, click the **Navigation menu** at the top-left.



Open the BigQuery console

1. In the Google Cloud Console, select **Navigation menu** > **BigQuery**.

The **Welcome to BigQuery in the Cloud Console** message box opens. This message box provides a link to the quickstart guide and the release notes.

2. Click **Done**.

The BigQuery console opens.

Task 1. Explore NYC taxi cab data

Question: How many trips did Yellow taxis take each month in 2015?

1. Copy and paste the following SQL code into the query **EDITOR**:

```
#standardSQL
SELECT
  TIMESTAMP_TRUNC(pickup_datetime,
    MONTH) month,
  COUNT(*) trips
FROM
  `bigquery-public-data.new_york.tlc_yellow_trips_2015`
GROUP BY
  1
ORDER BY
  1
```

content_c

2. Then click **Run**.

You should receive the following result:

month	trips
2015-01-01 00:00:00 UTC	12748986
2015-02-01 00:00:00 UTC	12450521
2015-03-01 00:00:00 UTC	13351609
2015-04-01 00:00:00 UTC	13071789
2015-05-01 00:00:00 UTC	13158262
2015-06-01 00:00:00 UTC	12324935
2015-07-01 00:00:00 UTC	11562783
2015-08-01 00:00:00 UTC	11130304
2015-09-01 00:00:00 UTC	11225063
2015-10-01 00:00:00 UTC	12315488
2015-11-01 00:00:00 UTC	11312676
2015-12-01 00:00:00 UTC	11460573

As we see, every month in 2015 had over 10 million NYC taxi trips—no small amount!

Test completed task

Click **Check my progress** to verify your performed task. If you have completed the task successfully, you will be granted with an assessment score.

Calculate trips taken by Yellow taxi in each month of 2015

Check my progress

Assessment Completed!

Question: What was the average speed of Yellow taxi trips in 2015?

- Replace the previous query with the following and then click **Run**:

```
#standardSQL
SELECT
  EXTRACT(HOUR
  FROM
    pickup_datetime) hour,
  ROUND(AVG(trip_distance / TIMESTAMP_DIFF(dropoff_datetime,
        pickup_datetime,
        SECOND))*3600, 1) speed
FROM
  `bigquery-public-data.new_york.tlc_yellow_trips_2015`
WHERE
  trip_distance > 0
  AND fare_amount/trip_distance BETWEEN 2
  AND 10
  AND dropoff_datetime > pickup_datetime
```

content_c

```
GROUP BY
  1
ORDER BY
  1
```

You should receive the following result:

hour	speed
0	15.8
1	16.3
2	16.8
3	17.5
4	20.0
5	21.6
6	17.6
7	13.7
8	11.6
9	11.4
10	11.5
11	11.3
12	11.2
13	11.3
14	11.2
15	11.0
16	11.5
17	11.2
18	11.1
19	11.8
20	12.9

During the day, the average speed is around 11-12 MPH; but at 5:00 AM the average speed almost doubles to 21 MPH. Intuitively this makes sense since there is likely less traffic on the road at 5:00 AM.

Test completed task

Click **Check my progress** to verify your performed task. If you have completed the task successfully, you will be granted with an assessment score.

Calculate the average speed of Yellow taxi trips in 2015

Check my progress

Assessment Completed!

Task 2. Identify an objective

You will now create a machine learning model in BigQuery to predict the price of a cab ride in New York City given the historical dataset of trips and trip data. Predicting the fare before the ride could be very useful for trip planning for both the rider and the taxi agency.

Task 3. Select features and create your training dataset

The New York City Yellow Cab dataset is a public dataset provided by the city and has been loaded into BigQuery for your exploration.

Browse the complete list of fields and then preview the dataset to find useful features that will help a machine learning model understand the relationship between data about historical cab rides and the price of the fare.

Your team decides to test whether these below fields are good inputs to your fare forecasting model:

- Tolls Amount
- Fare Amount
- Hour of Day
- Pick up address
- Drop off address
- Number of passengers

1. Replace the query with the following:

```
#standardSQL
WITH params AS (
    SELECT
    1 AS TRAIN,
    2 AS EVAL
    ),

  daynames AS
    (SELECT ['Sun', 'Mon', 'Tues', 'Wed', 'Thurs', 'Fri', 'Sat'] AS
daysofweek),

  taxitrips AS (
  SELECT
    (tolls_amount + fare_amount) AS total_fare,
```

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```
    daysofweek[ORDINAL(EXTRACT(DAYOFWEEK FROM pickup_datetime))] AS
dayofweek,
    EXTRACT(HOUR FROM pickup_datetime) AS hourofday,
    pickup_longitude AS pickuplon,
    pickup_latitude AS pickuplat,
    dropoff_longitude AS dropofflon,
    dropoff_latitude AS dropofflat,
    passenger_count AS passengers
  FROM
    `nyc-tlc.yellow.trips`, daynames, params
  WHERE
    trip_distance > 0 AND fare_amount > 0
    AND MOD(ABS(FARM_FINGERPRINT(CAST(pickup_datetime AS
STRING))),1000) = params.TRAIN
  )

  SELECT *
  FROM taxitrips
```

Note a few things about the query:

- The main part of the query is at the bottom (`SELECT * from taxitrips`).
- `taxitrips` does the bulk of the extraction for the NYC dataset, with the `SELECT` containing your training features and label.
- The `WHERE` removes data that you don't want to train on.
- The `WHERE` also includes a sampling clause to pick up only 1/1000th of the data.
- Define a variable called `TRAIN` so that you can quickly build an independent `EVAL` set.

2. Now that you have a better understanding of this query's purpose, click **Run**.

You should receive a similar result:

Query results SAVE RESULTS EXPLORE DATA

Query complete (8.1 sec elapsed, 74.3 GB processed)

Job information | Results | JSON | Execution details

Row	total_fare	dayofweek	hourofday	pickuplon	pickuplat	dropofflon	dropofflat	passengers
1	29.0	Sat	0	-73.992317	40.684042	-74.00993	40.603942	3
2	31.0	Fri	0	-73.98585	40.757277	-73.958277	40.676417	1
3	19.0	Tues	0	-73.989641	40.743882	-73.953406	40.718941	1
4	24.1	Sun	0	-73.982928	40.765147	-73.995246	40.68733	1

What is the label (correct answer)?

`total_fare` is the label (what you will be predicting). You created this field out of `tolls_amount` and `fare_amount`, so you could ignore customer tips as part of the model as they are discretionary.

Test completed task

Click **Check my progress** to verify your performed task. If you have completed the task successfully, you will be granted with an assessment score.

Test whether fields are good inputs to your fare forecasting model

Check my progress

Assessment Completed!

Task 4. Create a BigQuery dataset to store models

In this section, you will create a new BigQuery dataset which will store your ML models.

1. In the left-hand *Explorer* panel, click on the **View actions** icon next to your Project ID and then click **Create dataset**.

2. In the Create Dataset dialog, enter in the following:

- For **Dataset ID**, type **taxi**.
- Select **us(multiple regions in United States)** as the **Location type**.
- Leave the other values at their defaults.

3. Then click **Create dataset**.

Test completed task

Click **Check my progress** to verify your performed task. If you have completed the task successfully, you will be granted with an assessment score.

Create a BigQuery dataset to store models

Check my progress

Assessment Completed! BigQuery dataset created successfully. Dataset IDs: ["taxi"]

Task 5. Select a BigQuery ML model type and specify options

Now that you have your initial features selected, you are now ready to create your first ML model in BigQuery.

There are several model types to choose from:

- **Forecasting** numeric values like next month's sales with Linear Regression (linear_reg).
- Binary or Multiclass **Classification** like spam or not spam email by using Logistic Regression (logistic_reg).
- k-Means **Clustering** for when you want unsupervised learning for exploration (kmeans).

Note: There are many additional model types used in Machine Learning (like Neural Networks and decision trees) and available using libraries like TensorFlow. At this time, BQML supports the three listed above. Follow the BQML roadmap for more information.

Which model type should you choose for predicting taxi cab fare (numeric value)?

check Linear Regression

- Binary Classification
- SQL
- Multiclass Classification

Submit

1. Enter the following query to create a model and specify model options.

```
CREATE or REPLACE MODEL taxi.taxifare_model
OPTIONS
  (model_type='linear_reg', labels=['total_fare']) AS

WITH params AS (
    SELECT
    1 AS TRAIN,
    2 AS EVAL
    ),

  daynames AS
    (SELECT ['Sun', 'Mon', 'Tues', 'Wed', 'Thurs', 'Fri', 'Sat'] AS
daysofweek),

  taxitrips AS (
  SELECT
    (tolls_amount + fare_amount) AS total_fare,
```

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```
    daysofweek[ORDINAL(EXTRACT(DAYOFWEEK FROM pickup_datetime))] AS
dayofweek,
    EXTRACT(HOUR FROM pickup_datetime) AS hourofday,
    pickup_longitude AS pickuplon,
    pickup_latitude AS pickuplat,
    dropoff_longitude AS dropofflon,
    dropoff_latitude AS dropofflat,
    passenger_count AS passengers
  FROM
    `nyc-tlc.yellow.trips`, daynames, params
  WHERE
    trip_distance > 0 AND fare_amount > 0
    AND MOD(ABS(FARM_FINGERPRINT(CAST(pickup_datetime AS
STRING))),1000) = params.TRAIN
  )

  SELECT *
  FROM taxitrips
```

2. Next, click **Run** to train your model.

3. Wait for the model to train (5 - 10 minutes).

After your model is trained, you will see the message "This statement will create a new model named qwiklabs-gcp-03-xxxxxxxx:taxi.taxifare_model." which indicates that your model has been successfully trained.

4. Look inside your taxi dataset and confirm **taxifare_model** now appears.

Next, you will evaluate the performance of the model against new unseen evaluation data.

Test completed task

Click **Check my progress** to verify your performed task. If you have completed the task successfully, you will be granted with an assessment score.

Create a taxifare model

Check my progress

Assessment Completed!

Task 6. Evaluate classification model performance

Select your performance criteria

For linear regression models you want to use a loss metric like Root Mean Square Error (RMSE). You want to keep training and improving the model until it has the lowest RMSE.

In BQML, `mean_squared_error` is a queryable field when evaluating your trained ML model. Add a `SQRT()` to get RMSE.

Now that training is complete, you can evaluate how well the model performs with this query using `ML.EVALUATE`.

1. Copy and paste the following into the query **EDITOR** and click **Run**:

```
#standardSQL
SELECT
```

content_c

```
  SQRT(mean_squared_error) AS rmse
FROM
  ML.EVALUATE(MODEL taxi.taxifare_model,
  (

  WITH params AS (
    SELECT
    1 AS TRAIN,
    2 AS EVAL
    ),

  daynames AS
    (SELECT ['Sun', 'Mon', 'Tues', 'Wed', 'Thurs', 'Fri', 'Sat'] AS
daysofweek),

  taxitrips AS (
  SELECT
    (tolls_amount + fare_amount) AS total_fare,
    daysofweek[ORDINAL(EXTRACT(DAYOFWEEK FROM pickup_datetime))] AS
dayofweek,
    EXTRACT(HOUR FROM pickup_datetime) AS hourofday,
    pickup_longitude AS pickuplon,
    pickup_latitude AS pickuplat,
    dropoff_longitude AS dropofflon,
    dropoff_latitude AS dropofflat,
    passenger_count AS passengers
  FROM
    `nyc-tlc.yellow.trips`, daynames, params
  WHERE
    trip_distance > 0 AND fare_amount > 0
    AND MOD(ABS(FARM_FINGERPRINT(CAST(pickup_datetime AS
STRING))),1000) = params.EVAL
  )

  SELECT *
  FROM taxitrips

  ))
```

You are now evaluating the model against a different set of taxi cab trips with your `params.EVAL` filter.

2. After the model runs, review your model results (your model RMSE value will vary slightly).

Row	rmse
1	9.477056435999074

After evaluating your model you get a **RMSE** of 9.47. Since we took the Root of the Mean Squared Error (RMSE) the 9.47 error can be evaluated in the same units as the total_fare so it's +-$9.47.

Knowing whether or not this loss metric is acceptable to productionalize your model is entirely dependent on your benchmark criteria, which is set before model training begins. Benchmarking is establishing a minimum level of model performance and accuracy that is acceptable.

Test completed task

Click **Check my progress** to verify your performed task. If you have completed the task successfully, you will be granted with an assessment score.

Evaluate the classification model performance

Check my progress

Assessment Completed!

Task 7. Predict taxi fare amount

Next, write a query to use your new model to make predictions.

- Copy and paste the following into the query **EDITOR** and click **Run**:

content_c

```
#standardSQL
SELECT
*
FROM
  ml.PREDICT(MODEL `taxi.taxifare_model`,
   (

 WITH params AS (
    SELECT
    1 AS TRAIN,
    2 AS EVAL
    ),

  daynames AS
    (SELECT ['Sun', 'Mon', 'Tues', 'Wed', 'Thurs', 'Fri', 'Sat'] AS
daysofweek),

  taxitrips AS (
  SELECT
    (tolls_amount + fare_amount) AS total_fare,
    daysofweek[ORDINAL(EXTRACT(DAYOFWEEK FROM pickup_datetime))] AS
dayofweek,
    EXTRACT(HOUR FROM pickup_datetime) AS hourofday,
    pickup_longitude AS pickuplon,
    pickup_latitude AS pickuplat,
    dropoff_longitude AS dropofflon,
    dropoff_latitude AS dropofflat,
    passenger_count AS passengers
  FROM
    `nyc-tlc.yellow.trips`, daynames, params
  WHERE
    trip_distance > 0 AND fare_amount > 0
```

```
    AND MOD(ABS(FARM_FINGERPRINT(CAST(pickup_datetime AS
STRING))),1000) = params.EVAL
  )

  SELECT *
  FROM taxitrips

));
```

Now you will see the model's predictions for taxi fares alongside the actual fares and other features for those rides. Your results should look similar to those below:

Row	predicted_total_fare	total_fare	dayofweek	hourofday	pickuplon	pickuplat	dropofflon	dropofflat	passengers
1	11.688076703604127	4.0	Sun	0	-73.96526336669922	40.710994720458984	-73.96070861816406	40.7170524597168	1
2	11.762257540186688	4.5	Thurs	0	-73.985718	40.763036	-73.982686	40.771049	2
3	11.916452278036148	5.5	Sun	0	-73.998257	40.74529	-73.992132	40.740992	3
4	11.510321767563447	6.0	Tues	0	-74.00129	40.731077	-73.988967	40.745607	2

Test completed task

Click **Check my progress** to verify your performed task. If you have completed the task successfully, you will be granted with an assessment score.

Predict taxi fare amount

Check my progress

Assessment Completed!

Task 8. Improving the model with Feature Engineering

Building Machine Learning models is an iterative process. Once we have evaluated the performance of our initial model, we often go back and prune our features and rows to see if we can get an even better model.

Filtering the training dataset

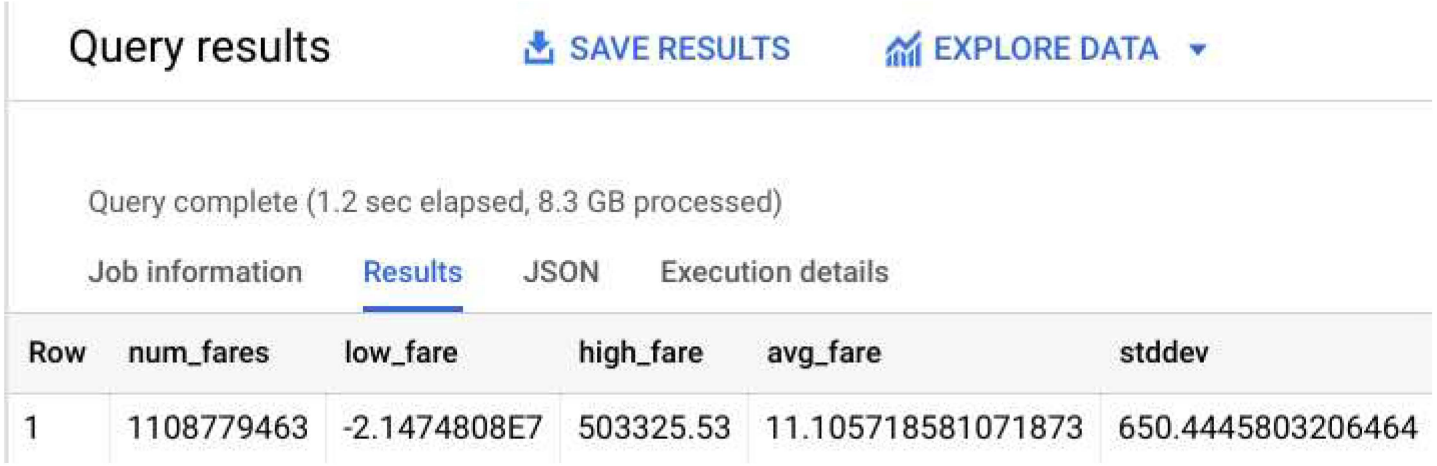
Now view the common statistics for taxi cab fares.

1. Copy and paste the following into the query **EDITOR** and click **Run**:

```
SELECT
  COUNT(fare_amount) AS num_fares,
  MIN(fare_amount) AS low_fare,
  MAX(fare_amount) AS high_fare,
  AVG(fare_amount) AS avg_fare,
  STDDEV(fare_amount) AS stddev
FROM
`nyc-tlc.yellow.trips`
# 1,108,779,463 fares
```

content_c

You should receive a similar output:



Row	num_fares	low_fare	high_fare	avg_fare	stddev
1	1108779463	-2.1474808E7	503325.53	11.105718581071873	650.4445803206464

As you can see, there are some strange outliers in our dataset (negative fares or fares over $50,000). Apply some of our subject matter expertise to help the model avoid learning on strange outliers.

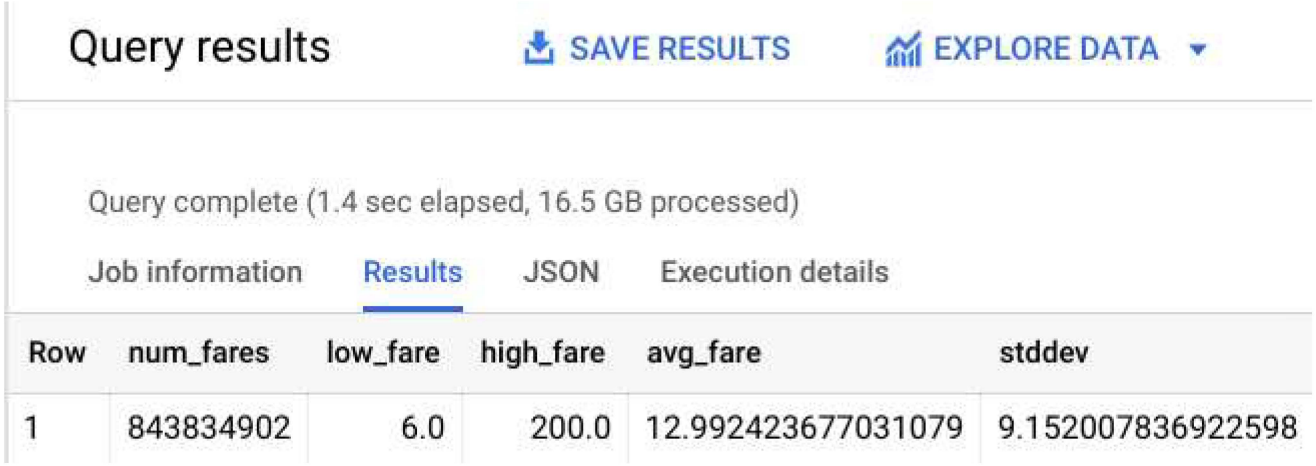
Limit the data to only fares between $$6 and $$200.

2. Copy and paste the following into the query **EDITOR** and click **Run**:

```
SELECT
  COUNT(fare_amount) AS num_fares,
  MIN(fare_amount) AS low_fare,
  MAX(fare_amount) AS high_fare,
  AVG(fare_amount) AS avg_fare,
  STDDEV(fare_amount) AS stddev
FROM
`nyc-tlc.yellow.trips`
WHERE trip_distance > 0 AND fare_amount BETWEEN 6 and 200
# 843,834,902 fares
```

content_c

You should receive a similar output:



Row	num_fares	low_fare	high_fare	avg_fare	stddev
1	843834902	6.0	200.0	12.992423677031079	9.152007836922598

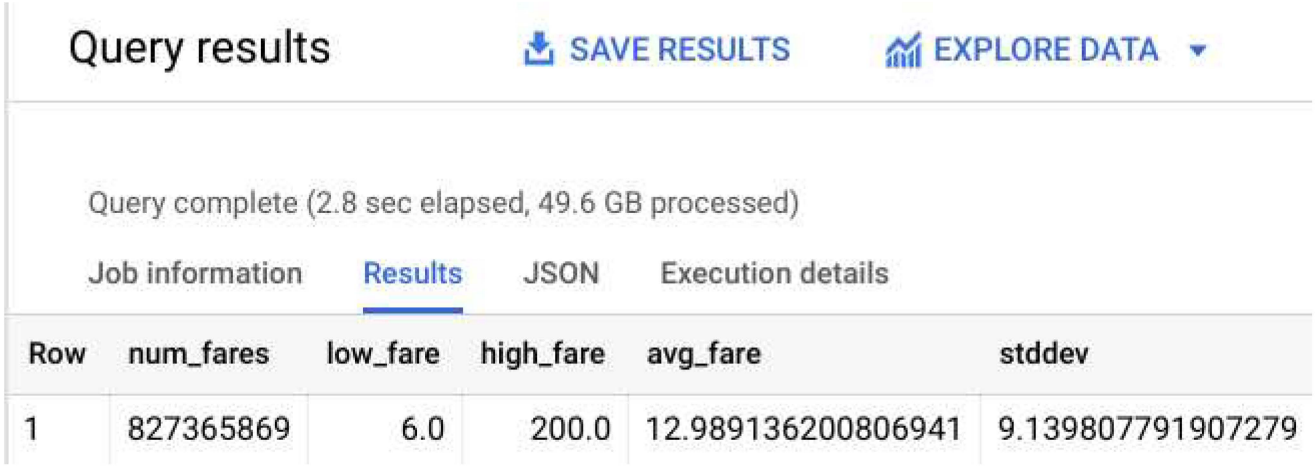
That's a little bit better. While you're at it, limit the distance traveled so you're really focusing on New York City.

3. Copy and paste the following into the query **EDITOR** and click **Run**:

```
SELECT
  COUNT(fare_amount) AS num_fares,
  MIN(fare_amount) AS low_fare,
  MAX(fare_amount) AS high_fare,
  AVG(fare_amount) AS avg_fare,
  STDDEV(fare_amount) AS stddev
FROM
`nyc-tlc.yellow.trips`
WHERE trip_distance > 0 AND fare_amount BETWEEN 6 and 200
    AND pickup_longitude > -75 #limiting of the distance the taxis
travel out
    AND pickup_longitude < -73
    AND dropoff_longitude > -75
    AND dropoff_longitude < -73
    AND pickup_latitude > 40
    AND pickup_latitude < 42
    AND dropoff_latitude > 40
    AND dropoff_latitude < 42
    # 827,365,869 fares
```

content_c

You should receive a similar output:



Row	num_fares	low_fare	high_fare	avg_fare	stddev
1	827365869	6.0	200.0	12.989136200806941	9.139807791907279

You still have a large training dataset of over 800 million rides for our new model to learn from. Re-train the model with these new constraints and see how well it performs.

Retraining the model

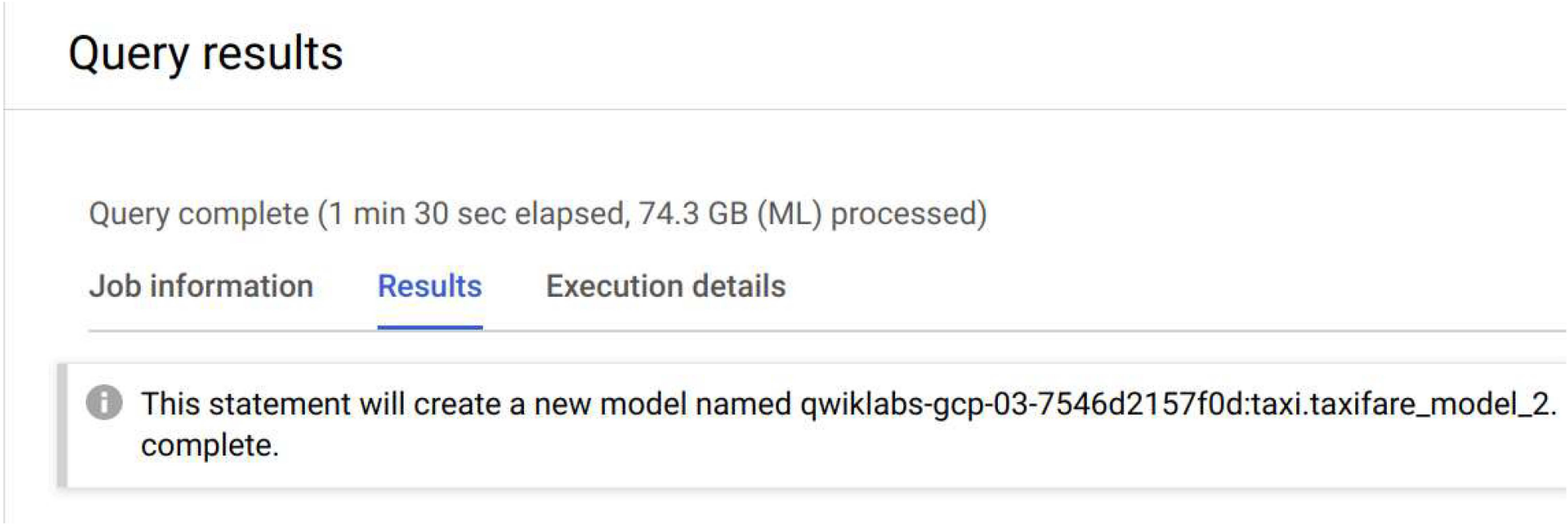
Call the new model `taxi.taxifare_model_2` and retrain the linear regression model to predict total fare. You'll note that you've also added a few calculated features for the Euclidean distance (straight line) between the pick up and drop off.

- Copy and paste the following into the query **EDITOR** and click **Run**:

```
CREATE OR REPLACE MODEL taxi.taxifare_model_2
OPTIONS
  (model_type='linear_reg', labels=['total_fare']) AS


WITH params AS (
    SELECT
```

```
    1 AS TRAIN,
    2 AS EVAL
    ),

  daynames AS
    (SELECT ['Sun', 'Mon', 'Tues', 'Wed', 'Thurs', 'Fri', 'Sat'] AS
daysofweek),

  taxitrips AS (
  SELECT
    (tolls_amount + fare_amount) AS total_fare,
    daysofweek[ORDINAL(EXTRACT(DAYOFWEEK FROM pickup_datetime))] AS
dayofweek,
    EXTRACT(HOUR FROM pickup_datetime) AS hourofday,
    SQRT(POW((pickup_longitude - dropoff_longitude),2) + POW((
pickup_latitude - dropoff_latitude), 2)) as dist, #Euclidean distance
between pickup and drop off
    SQRT(POW((pickup_longitude - dropoff_longitude),2)) as longitude,
#Euclidean distance between pickup and drop off in longitude
    SQRT(POW((pickup_latitude - dropoff_latitude), 2)) as latitude,
#Euclidean distance between pickup and drop off in latitude
    passenger_count AS passengers
  FROM
    `nyc-tlc.yellow.trips`, daynames, params
WHERE trip_distance > 0 AND fare_amount BETWEEN 6 and 200
    AND pickup_longitude > -75 #limiting of the distance the taxis
travel out
    AND pickup_longitude < -73
    AND dropoff_longitude > -75
    AND dropoff_longitude < -73
    AND pickup_latitude > 40
    AND pickup_latitude < 42
    AND dropoff_latitude > 40
    AND dropoff_latitude < 42
    AND MOD(ABS(FARM_FINGERPRINT(CAST(pickup_datetime AS
STRING))),1000) = params.TRAIN
  )

  SELECT *
  FROM taxitrips
```

It may take a couple minutes to retrain the model. You can move onto the next step when you receive the following message in the Console:



Evaluate the new model

Now that the linear regression model has been optimized, evaluate the dataset with it and see how it performs.

- Copy and paste the following into the query **EDITOR** and click **Run**:

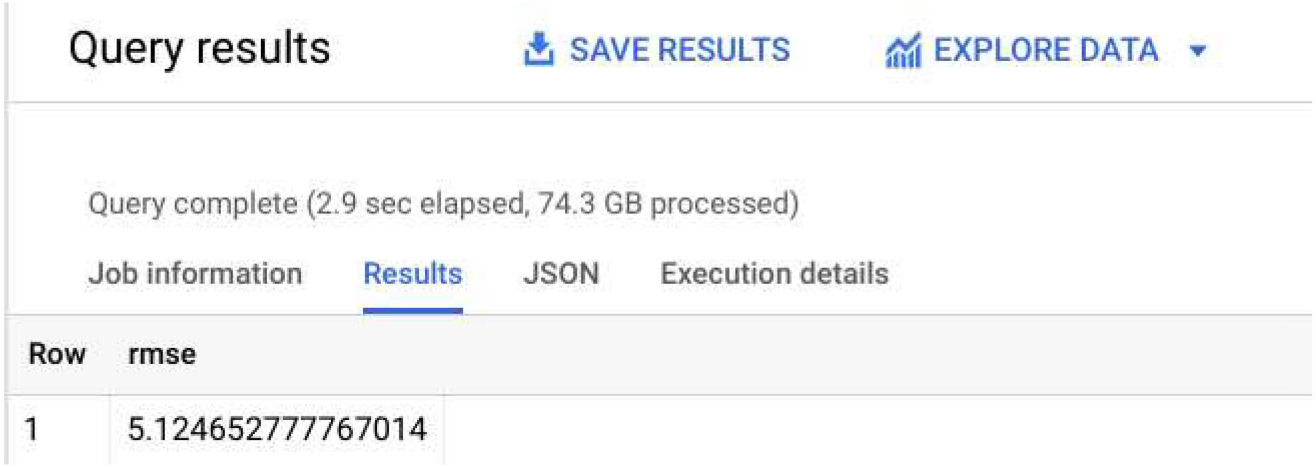
```
SELECT
  SQRT(mean_squared_error) AS rmse
FROM
  ML.EVALUATE(MODEL taxi.taxifare_model_2,
  (

  WITH params AS (
```

content_c

```
    SELECT
    1 AS TRAIN,
    2 AS EVAL
    ),

  daynames AS
    (SELECT ['Sun', 'Mon', 'Tues', 'Wed', 'Thurs', 'Fri', 'Sat'] AS
daysofweek),

  taxitrips AS (
  SELECT
    (tolls_amount + fare_amount) AS total_fare,
    daysofweek[ORDINAL(EXTRACT(DAYOFWEEK FROM pickup_datetime))] AS
dayofweek,
    EXTRACT(HOUR FROM pickup_datetime) AS hourofday,
    SQRT(POW((pickup_longitude - dropoff_longitude),2) + POW((
pickup_latitude - dropoff_latitude), 2)) as dist, #Euclidean distance
between pickup and drop off
    SQRT(POW((pickup_longitude - dropoff_longitude),2)) as longitude,
#Euclidean distance between pickup and drop off in longitude
    SQRT(POW((pickup_latitude - dropoff_latitude), 2)) as latitude,
#Euclidean distance between pickup and drop off in latitude
    passenger_count AS passengers
  FROM
    `nyc-tlc.yellow.trips`, daynames, params
WHERE trip_distance > 0 AND fare_amount BETWEEN 6 and 200
    AND pickup_longitude > -75 #limiting of the distance the taxis
travel out
    AND pickup_longitude < -73
    AND dropoff_longitude > -75
    AND dropoff_longitude < -73
    AND pickup_latitude > 40
    AND pickup_latitude < 42
    AND dropoff_latitude > 40
    AND dropoff_latitude < 42
    AND MOD(ABS(FARM_FINGERPRINT(CAST(pickup_datetime AS
STRING))),1000) = params.EVAL
  )

  SELECT *
  FROM taxitrips
```

```
))
```

You should receive a similar output:



As you see, you've gotten the RMSE down to: +-$$5.12 which is significantly better than +-$$9.47 for your first model.

Since RMSE defines the standard deviation of prediction errors, we see that the retrained linear regression made our model a lot more accurate.

Task 9. Test your understanding

Below are multiple choice questions to reinforce your understanding of this lab's concepts. Answer them to the best of your abilities.

A lower RMSE value usually indicates a more accurate BQML model.

- False
- check True

Submit

Task 10. Other datasets to explore

You can use the **bigquery-public-data** project if you want to explore modeling on other datasets like forecasting fares for Chicago taxi trips.

1. To open the **bigquery-public-data** dataset, click **+Add** > **Star a project by name** > **Enter Project Name**, then write the `bigquery-public-data` name.

2. Click **Star**.

The `bigquery-public-data` project is listed in the Explorer section.

Congratulations!

You've successfully built