05

# Custom Model Building with SQL in BigQuery ML

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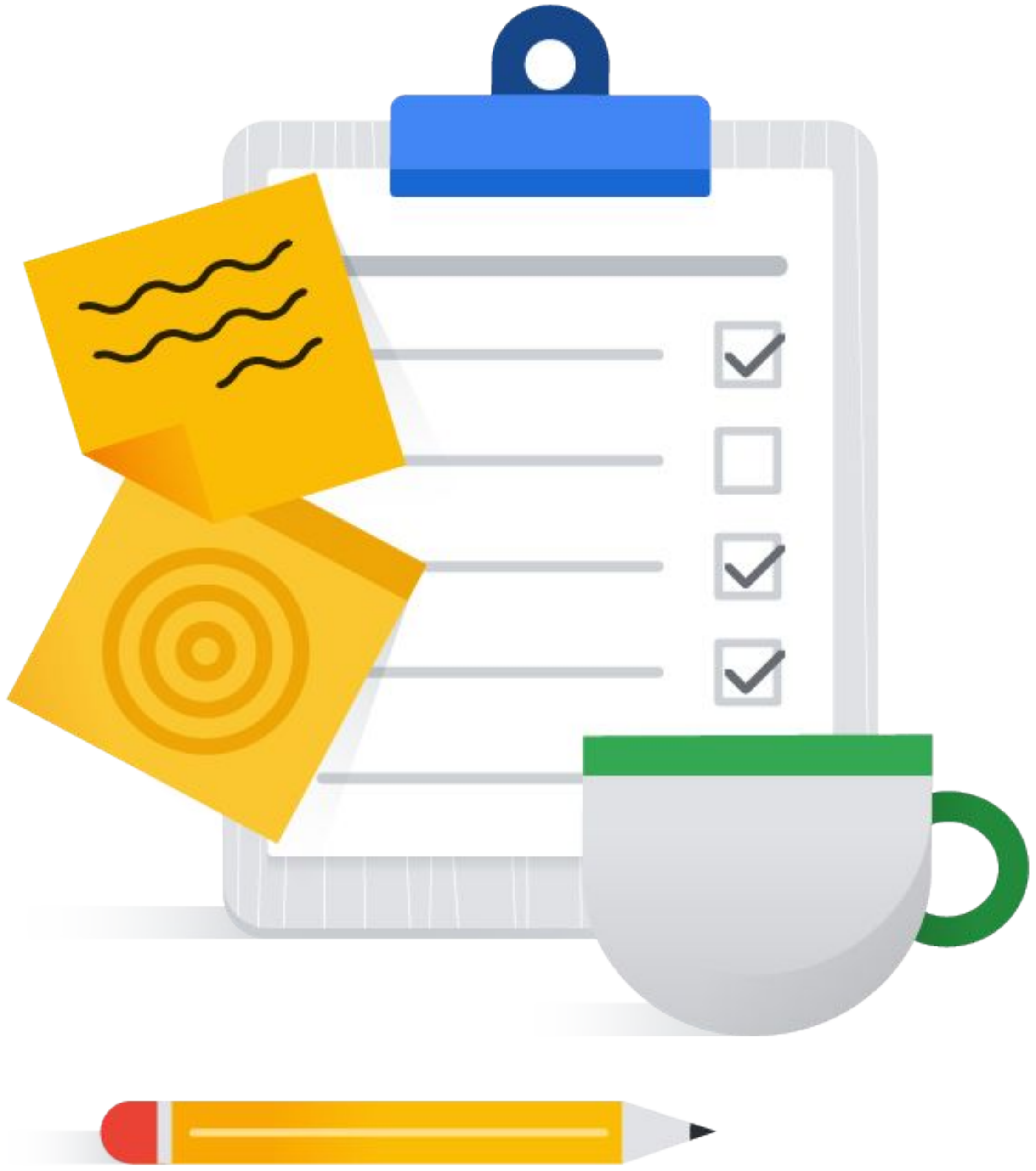
| | |
|---|---|
| 01 | BigQuery ML for quick model building |
| 02 | Supported models |



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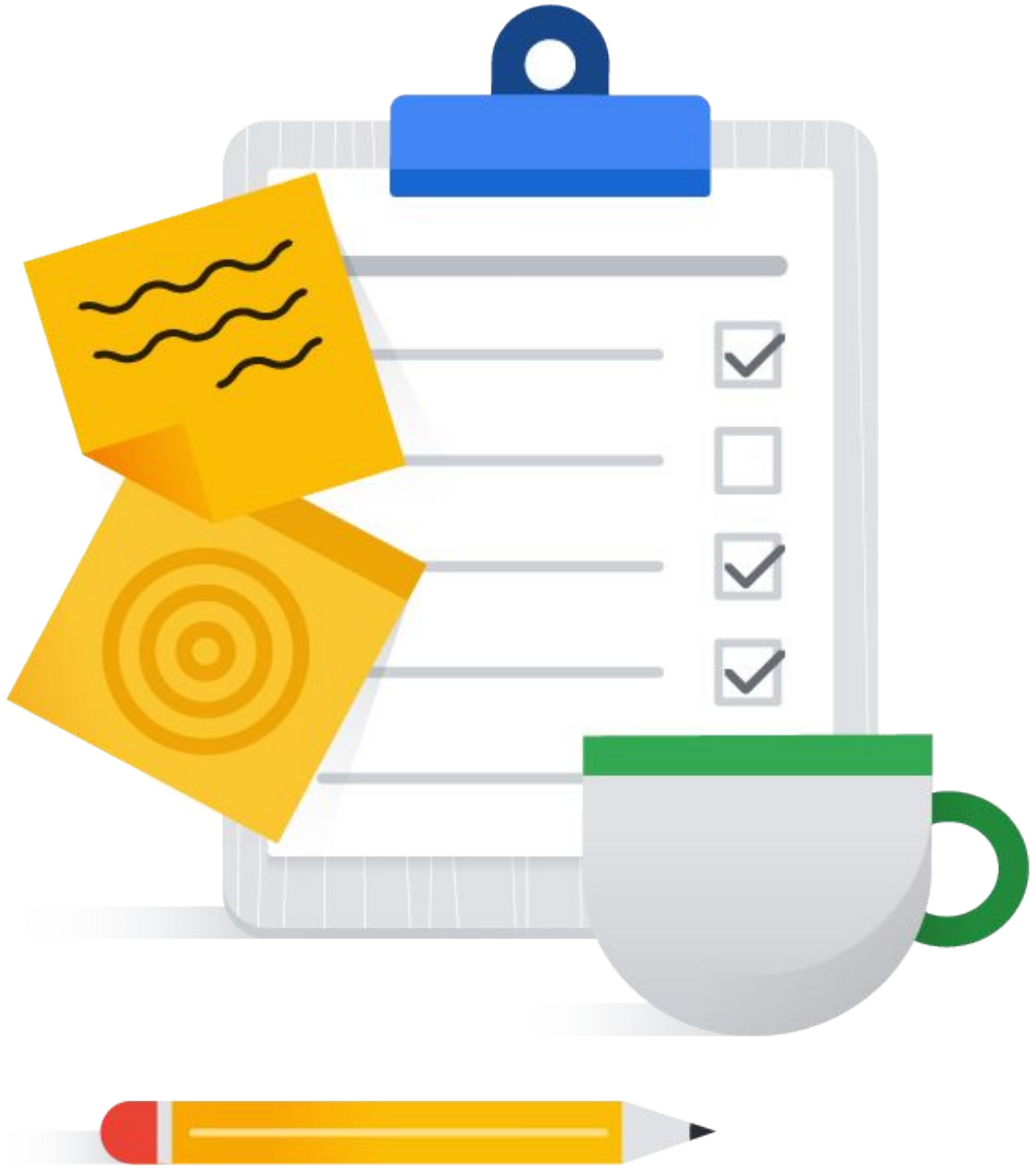
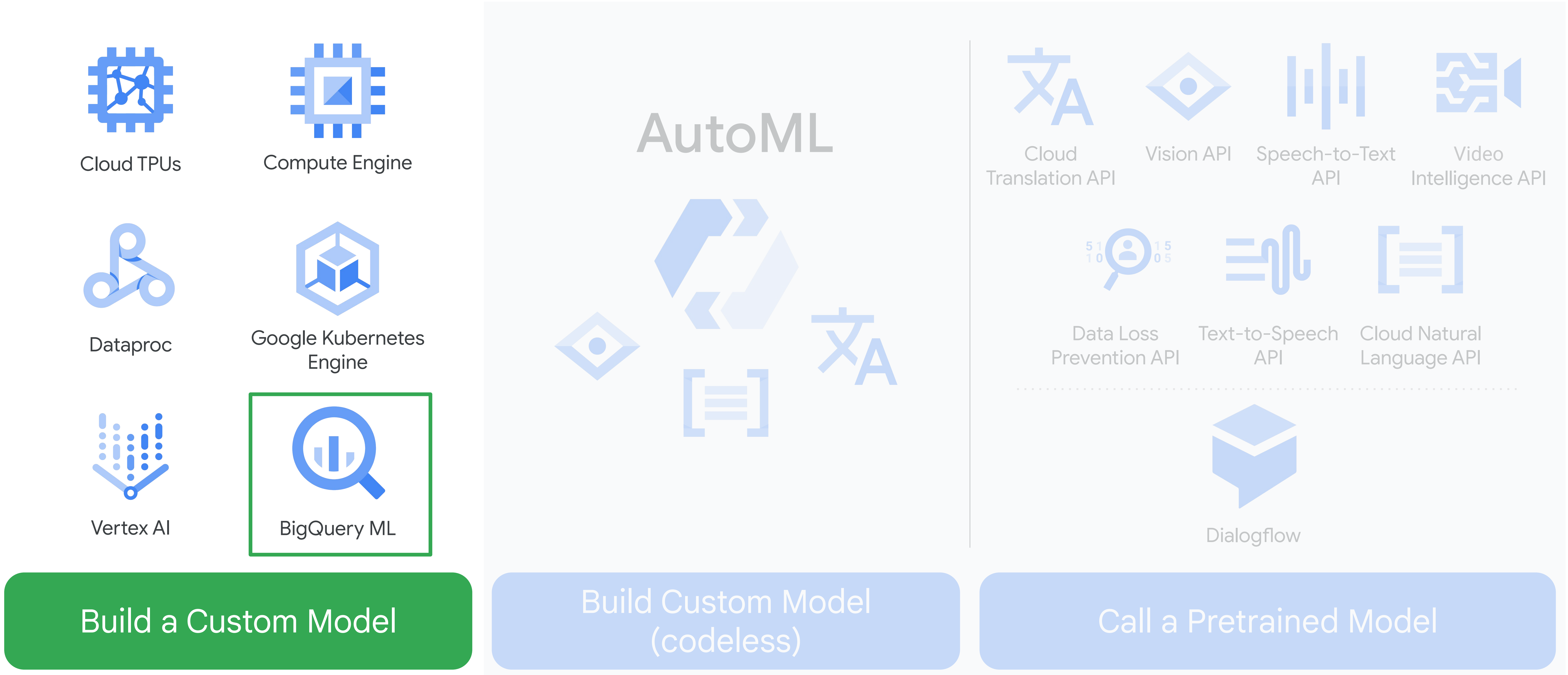


# BigQuery ML is a way to build custom models



# BigQuery ML is a way to build custom models

Cloud TPUs

Compute Engine

Dataproc

Google Kubernetes Engine

Vertex AI

BigQuery ML

**Build a Custom Model**

## AutoML

**Build Custom Model (codeless)**

Cloud Translation API

Vision API

Speech-to-Text API

Video Intelligence API

Data Loss Prevention API

Text-to-Speech API

Cloud Natural Language API

Dialogflow

**Call a Pretrained Model**

# Working with BigQuery ML

1 Dataset

2 Create/train

```
CREATE MODEL `bqml_tutorial.sample_model`
OPTIONS(model_type='logistic_reg') AS
SELECT
```

3 Evaluate

```
FROM
  ML.EVALUATE(MODEL
`bqml_tutorial.sample_model`,
    TABLE eval_table)
```

4 Predict/classify

```
FROM
    ML.PREDICT(MODEL
`bqml_tutorial.sample_model`,
      table game_to_predict) ) AS
predict
```

# Where was this article published?

1. Techcrunch
2. GitHub
3. NY Times

**Unlikely Partnership in House Gives Lawmakers Hope for Border Deal**

Representatives Nita M. Lowey and Kay Granger are the first women to lead the House Appropriations Committee. Their bond gives lawmakers optimism for the work to come.

By EMILY COCHRANE

**Fitbit's newest fitness tracker is just for employees and health insurance members**

Fitbit has a new fitness tracker, but it's one that you can't buy in stores. The company quietly uncorked the Inspire on Friday, releasing its first product that is available only to co...

1 hour ago **Jon Russell**

## Downloading the Android Studio Project Folder

FTC Engineering edited this page on Sep 19, 2017 · 1 revision

**Downloading the Android Studio Project Folder**

# SQL query to extract data

```
SELECT
  url, title
FROM
  `bigquery-public-data.hacker_news.stories`
WHERE
  LENGTH(title) > 10
  AND LENGTH(url) > 0
LIMIT 10
```

| url | title |
|---|---|
| http://www.bbc.co.uk/news/business-27732743 | Vodafone reveals direct government wiretaps |
| https://www.kickstarter.com/projects/appdocu/a... | Doc – App: The Human Story |
| http://www.starwebworld.com/android-jelly-bean... | Android Jelly Bean: Streaming Audio Through th... |
| http://www.myplanetdigital.com/digital_strateg... | Why Canadian Tech Entrepreneurs Need to Man/Wo... |
| http://startupislandconference.com/index.html | StartupConference June 13. - 16. 2013, HVAR Cr... |
| http://kopimism.org/ | Kopimism Hactivism Meetup Tomorrow (Sunday) in... |
| http://unearthedgadget.com/xbox-live-gold-2/14... | Xbox Live Gold Membership Is It Really Worth -... |
| https://evertale.com | Evertale changes the way people remember |
| http://www.racketboy.com/retro/commodore-amiga... | Commodore Amiga: A Beginner's Guide |
| http://www.extremetech.com/extreme/156393-cold... | Cold fusion reactor "independently verified" |

*no clusters, no indexes, ad hoc query!

# Use regex to get source + train on words of title

txtclass_words

LINK SHARING

```sql
WITH extracted AS (
SELECT source, REGEXP_REPLACE(LOWER(REGEXP_REPLACE(title, '[^a-zA-Z0-9 $.-]', ' ')), "  "
FROM
  (SELECT
    ARRAY_REVERSE(SPLIT(REGEXP_EXTRACT(url, '.*://(.[^/]+)/'), '.'))[OFFSET(1)] AS source
    title
  FROM
    `bigquery-public-data.hacker_news.stories`
  WHERE
    REGEXP_CONTAINS(REGEXP_EXTRACT(url, '.*://(.[^/]+)/'), '.com$')
    AND LENGTH(title) > 10
  )
)
, ds AS (
SELECT ARRAY_CONCAT(SPLIT(title, " "), ['NULL', 'NULL', 'NULL', 'NULL', 'NULL']) AS words
extracted
WHERE (source = 'github' OR source = 'nytimes' OR source = 'techcrunch')
)
SELECT
source,
words[OFFSET(0)] AS word1,
words[OFFSET(1)] AS word2,
words[OFFSET(2)] AS word3,
words[OFFSET(3)] AS word4,
words[OFFSET(4)] AS word5
FROM ds
```

Run | Save query | Save view | More

This query will process 204

Query results

SAVE RESULTS

EXPLORE IN DATA STUDIO

| | | | | | | |
|---|---|---|---|---|---|---|
| 37293 | nytimes | the | socratic | shrink | NULL | NULL |
| 37294 | nytimes | still | stuck | in | a | climate |
| 37295 | nytimes | as | unlimited | data | plans | are |
| 37296 | nytimes | disney | s | neuroscience | advertising | lab |
| 37297 | nytimes | hold | that | thought | the | google |

# Create model

Query to extract training data

```
CREATE OR REPLACE MODEL advdata.txtclass
OPTIONS(model_type='logistic_reg', input_label_cols=['source'])
AS

WITH extracted AS (
...
)
, ds AS (
SELECT ARRAY_CONCAT(SPLIT(title, " "), ['NULL', 'NULL', 'NULL',
'NULL', 'NULL']) AS words, source FROM extracted
WHERE (source = 'github' OR source = 'nytimes' OR source =
'techcrunch')
)


SELECT
source,
words[OFFSET(0)] AS word1,
words[OFFSET(1)] AS word2,
words[OFFSET(2)] AS word3,
words[OFFSET(3)] AS word4,
words[OFFSET(4)] AS word5
FROM ds
```

# Evaluate model

```
SELECT * FROM ML.EVALUATE(MODEL advdata.txtclass)
```

| precision | recall | accuracy | f1_score | log_loss | roc_auc |
|---|---|---|---|---|---|
| 0.783 | 0.783 | 0.79 | 0.783 | 0.858 | 0.918 |

| Actual labels \ Predicted labels | github | nytimes | techcrunch | % samples |
|---|---|---|---|---|
| github | 88.8% | 5.29% | 5.9% | 37.83% |
| nytimes | 6.34% | 70.92% | 22.74% | 31.26% |
| techcrunch | 5.54% | 19.35% | 75.11% | 30.9% |

*(BigQuery ML splits the training data and reports evaluation statistics on the held-out set)*

# Predict using trained model

```
SELECT * FROM ML.PREDICT(MODEL advdata.txtclass,(
     SELECT 'government' AS word1, 'shutdown' AS word2, 'leaves' AS word3,
'workers' AS word4, 'reeling' AS word5
     UNION ALL SELECT 'unlikely', 'partnership', 'in', 'house', 'gives'
     UNION ALL SELECT 'fitbit', 's', 'fitness', 'tracker', 'is'
     UNION ALL SELECT 'downloading', 'the', 'android', 'studio', 'project'
))
```

"Batch prediction"

| Row | Predicted_source | word1 | word2 | word3 | word4 | word5 |
|---|---|---|---|---|---|---|
| 1 | nytimes | government | shutdown | leaves | workers | reeling |
| 2 | nytimes | unlikely | partnership | in | house | gives |
| 3 | techcrunch | fitbit | s | fitness | tracker | is |
| 4 | techcrunch | downloading | the | android | studio | project |

# Demo

Train a model with BigQuery ML
to predict NYC taxi fares

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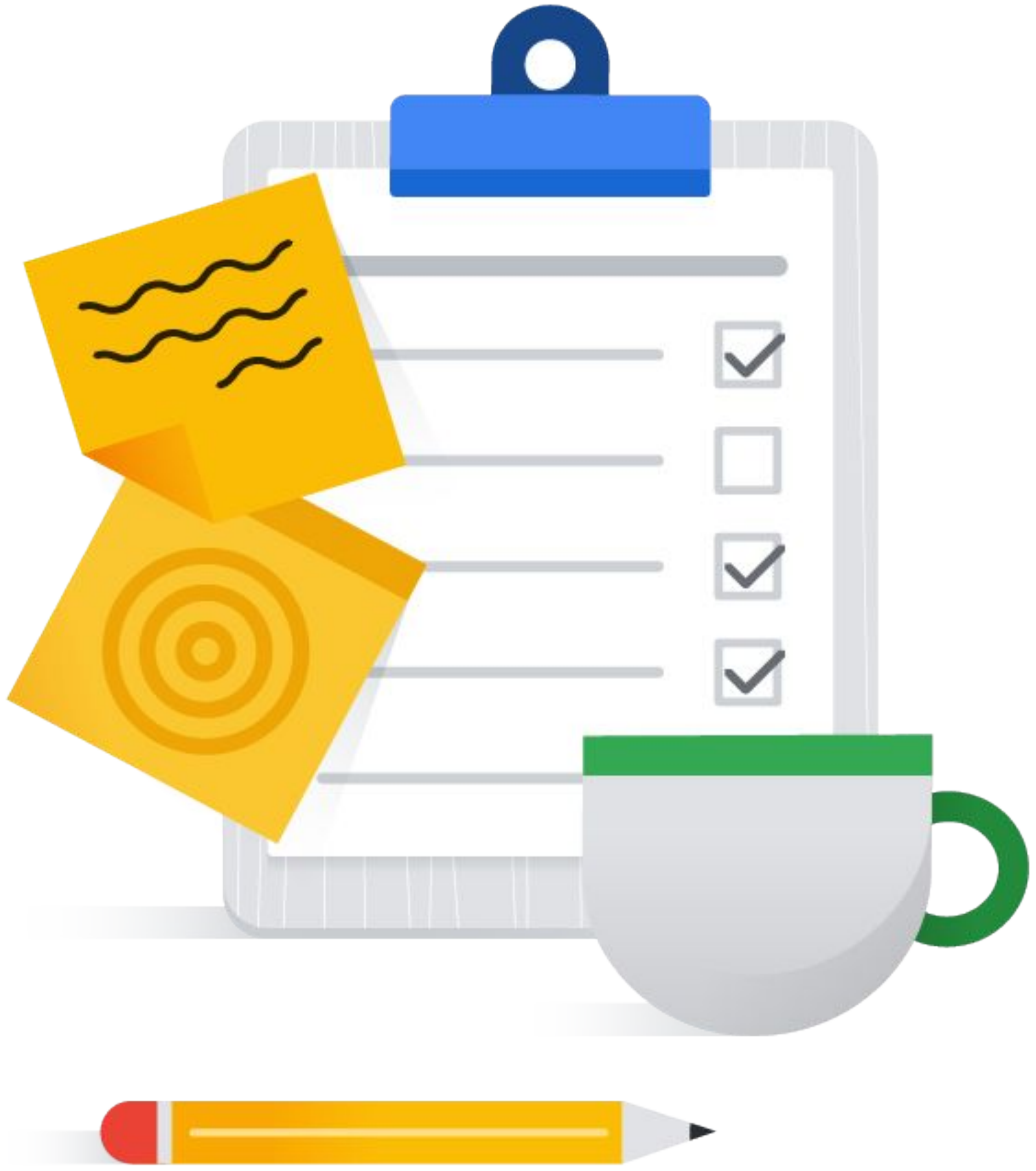


# Linear Classifier (Logistic regression)

```
#standardsql
CREATE OR REPLACE MODEL flights.ontime
OPTIONS
   (model_type='logistic_reg', input_label_cols=['on_time']) AS
SELECT
   IF(arr_delay < 15, 1, 0) AS on_time,
   carrier,
   origin,
   dest,
   dep_delay,
   taxi_out,
   distance
FROM
   `cloud-training-demos.flights.tzcorr`
WHERE
   arr_delay IS NOT NULL
```

# DNN Classifier

```
#standardsql
CREATE OR REPLACE MODEL flights.ontime
OPTIONS
   (model_type='dnn_classifier', hidden_units = [47,29,18],
   input_label_cols=['on_time']) AS
SELECT
   IF(arr_delay < 15, 1, 0) AS on_time,
   carrier,
   origin,
   dest,
   dep_delay,
   taxi_out,
   distance
FROM
   `cloud-training-demos.flights.tzcorr`
WHERE
   arr_delay IS NOT NULL
```

# xgboost Classifier

```
#standardsql
CREATE OR REPLACE MODEL flights.ontime
OPTIONS
   (model_type='boosted_tree_classifier', input_label_cols=['on_time']) AS
SELECT
   IF(arr_delay < 15, 1, 0) AS on_time,
   carrier,
   origin,
   dest,
   dep_delay,
   taxi_out,
   distance
FROM
   `cloud-training-demos.flights.tzcorr`
WHERE
   arr_delay IS NOT NULL
```

# Linear Regression

```
CREATE OR REPLACE MODEL
   taxi.taxifare_dnn OPTIONS (model_type='linear_reg', labels=['fare_amount']) AS
SELECT
   fare_amount,
   hourofday, dayofweek,
   pickuplon, pickuplat, dropofflon, dropofflat,
   passenger_count
FROM
   `taxi.taxi3m`
```

# DNN Regression

```
CREATE OR REPLACE MODEL
   taxi.taxifare_dnn OPTIONS (model_type='dnn_regressor',
   hidden_units=[144,89,55], labels=['fare_amount']) AS
SELECT
   fare_amount,
   hourofday, dayofweek,
   pickuplon, pickuplat, dropofflon, dropofflat,
   passenger_count
FROM
   `taxi.taxi3m`
```

# xgboost Regression

```
CREATE OR REPLACE MODEL
   taxi.taxifare_xgboost
   OPTIONS (model_type='boosted_tree_regressor', labels=['fare_amount']) AS
SELECT
   fare_amount,
   hourofday, dayofweek,
   pickuplon, pickuplat, dropofflon, dropofflat,
   passenger_count
FROM
   `taxi.taxi3m`
```

# Train on TF, predict with BigQuery

```
CREATE OR REPLACE MODEL advdata.txtclass_tf2
OPTIONS (model_type='tensorflow',

model_path='gs://cloud-training-demos-ml/txtcls/trained_finetune_native/export/exporter/1
549825580/*')
```

```
SELECT
  input,
  (SELECT AS STRUCT(p, ['github', 'nytimes', 'techcrunch'][ORDINAL(s)]) prediction FROM
    (SELECT p, ROW_NUMBER() OVER() AS s FROM
      (SELECT * FROM UNNEST(dense_1) AS p))
  ORDER BY p DESC LIMIT 1).*

FROM ML.PREDICT(MODEL advdata.txtclass_tf2,
(
SELECT 'Unlikely Partnership in House Gives Lawmakers Hope for Border Deal' AS input
UNION ALL SELECT "Fitbit\'s newest fitness tracker is just for employees and health
insurance members"
UNION ALL SELECT "Show HN: Hello, a CLI tool for managing social media"
))
```

# Recommendation engine (matrix factorization)

```
create or replace model models.suggested_products_1or2_example
options(model_type='matrix_factorization',
        user_col='user_id', item_col='product_id', rating_col='rating',
        l2_reg=10)
AS

with purchases AS (
 select product_id, user_id from
 operations.orders_with_lines, unnest(order_lines)
),

total_purchases as (
select product_id, user_id, count(*) as numtimes
from purchases
group by product_id, user_id
)

select
product_id, user_id,
IF(numtimes < 2, 1, 2) AS rating
FROM total_purchases
```

# So what do we recommend for a given set of users?

```
with users AS (
SELECT
user_id, count(*) as num_orders
from operations.orders_with_lines
group by user_id
order by num_orders desc
limit 10
),

products as (
select product_id, count(*) as num_orders
from operations.orders_with_lines, unnest(order_lines)
group by product_id
order by num_orders desc
limit 10
)

SELECT * FROM ML.PREDICT(MODEL models.suggested_products_1or2,
(SELECT user_id, product_id
FROM users, products)
)
```

# So what do we recommend for a given set of users?

| Row | predicted_rating | user_id | product_id |
|---|---|---|---|
| 1 | 1.5746015507788755 | 101797 | 26209 |
| 2 | 1.8070705987455633 | 101797 | 13176 |
| 3 | 1.7171094544245578 | 101797 | 27845 |
| 4 | 1.9763373899260837 | 101797 | 47209 |
| 5 | 1.8659380090171271 | 101797 | 21137 |
| 6 | 1.7216108485300093 | 101797 | 47766 |
| 7 | 1.9516130703939483 | 101797 | 21903 |

# Clustering

```
CREATE OR REPLACE MODEL
demos_eu.london_station_clusters
OPTIONS(model_type='kmeans', num_clusters=4,
standardize_features = true) AS


WITH hs AS …,
stationstats AS …

SELECT * except(station_name, isweekday)
from stationstats
```

1. 4 clusters (hardcoded)
2. Standardize features since different dynamic ranges
3. Remove the cluster “id” fields (keep just the attributes)

# Which cluster?

```
WITH hs AS ...,
stationstats AS ...,

SELECT * except(nearest_centroids_distance)
FROM ML.PREDICT(MODEL demos_eu.london_station_clusters,
(SELECT * FROM stationstats WHERE
REGEXP_CONTAINS(station_name, 'Kennington')))
```

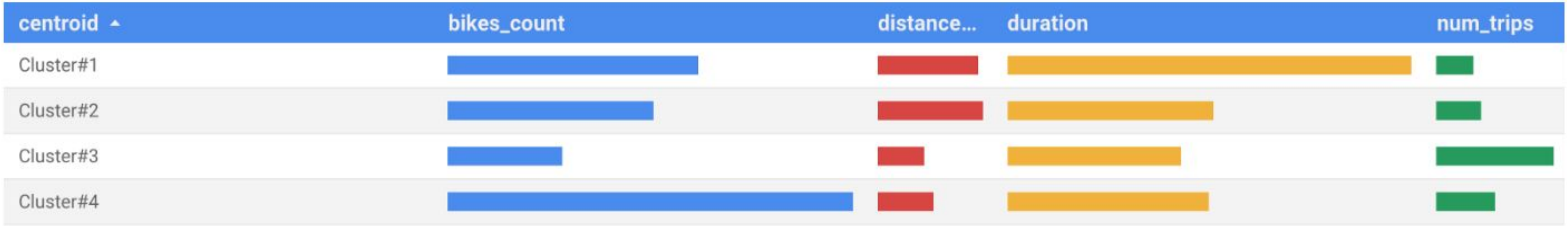
| Row | CENTROID_ID | station_name | isweekday | duration | num_trips | bikes_count | distance_from_city_center |
|---|---|---|---|---|---|---|---|
| 1 | 3 | Kennington Lane Tesco, Vauxhall | weekday | 911.5810637908974 | 5471 | 9 | 1.8345619962343163 |
| 2 | 3 | Kennington Lane Rail Bridge, Vauxhall | weekday | 979.3919952622995 | 20263 | 19 | 2.175032834765301 |
| 3 | 4 | Doddington Grove, Kennington | weekday | 1397.7189755200225 | 7067 | 28 | 1.468140527379382 |
| 4 | 4 | Kennington Cross, Kennington | weekday | 911.5238777770538 | 15349 | 35 | 1.4625875338501981 |

# Find cluster attributes

```
WITH T AS (
SELECT
centroid_id,
ARRAY_AGG(STRUCT(numerical_feature AS name, ROUND(feature_value,1) AS value) ORDER BY
centroid_id) AS cluster
FROM ML.CENTROIDS(MODEL demos_eu.london_station_clusters)
GROUP BY centroid_id
)
SELECT
CONCAT('Cluster#', CAST(centroid_id AS STRING)) AS centroid,
(SELECT value from unnest(cluster) WHERE name = 'duration') AS duration,
(SELECT value from unnest(cluster) WHERE name = 'num_trips') AS num_trips,
(SELECT value from unnest(cluster) WHERE name = 'bikes_count') AS bikes_count,
(SELECT value from unnest(cluster) WHERE name = 'distance_from_city_center') AS
distance_from_city_center
FROM T
ORDER BY centroid_id ASC
```

# Visualize attributes in Google Data Studio

| Row | centroid | duration | num_trips | bikes_count | distance_from_city_center |
|---|---|---|---|---|---|
| 1 | Cluster#1 | 3079.5 | 3026.1 | 14.0 | 6.2 |
| 2 | Cluster#2 | 1564.0 | 3635.1 | 11.5 | 6.5 |
| 3 | Cluster#3 | 1319.6 | 9654.8 | 6.4 | 2.9 |
| 4 | Cluster#4 | 1527.7 | 4846.8 | 22.6 | 3.5 |



# Reminder: BigQuery ML Cheatsheet

- **Label =** `alias a column as 'label' or specify column in OPTIONS using input_label_cols`
- **Feature =** passed through to the model as part of your SQL SELECT statement
  `SELECT * FROM ML.FEATURE_INFO(MODEL `mydataset.mymodel`)`
- **Model =** an object created in BigQuery that resides in your BigQuery dataset
- **Model Types =** Linear Regression, Logistic Regression
  ```
  CREATE OR REPLACE MODEL <dataset>.<name>
  OPTIONS(model_type='<type>') AS
  <training dataset>
  ```
- **Training Progress =** `SELECT * FROM ML.TRAINING_INFO(MODEL `mydataset.mymodel`)`
- **Inspect Weights =** `SELECT * FROM ML.WEIGHTS(MODEL `mydataset.mymodel`, (<query>))`
- **Evaluation =** `SELECT * FROM ML.EVALUATE(MODEL `mydataset.mymodel`)`
- **Prediction =** `SELECT * FROM ML.PREDICT(MODEL `mydataset.mymodel`, (<query>))`

# Lab Intro

Predict Bike Trip Duration with a Regression Model in BigQuery ML

# Lab objectives

01 Query and explore the London bicycles dataset for feature engineering

02 Create a linear regression model in BigQuery ML

03 Evaluate the performance of your machine learning model

04 Extract your model weights

# Lab Intro

Movie Recommendations in BigQuery ML

# Lab objectives

01 Create a BigQuery dataset to store and load MovieLens data

02 Explore the MovieLens dataset

03 Use a trained model to make recommendations in BigQuery

04 Make product predictions for both single users and batch users

# Summary

You can train and evaluate machine learning models directly in BigQuery.