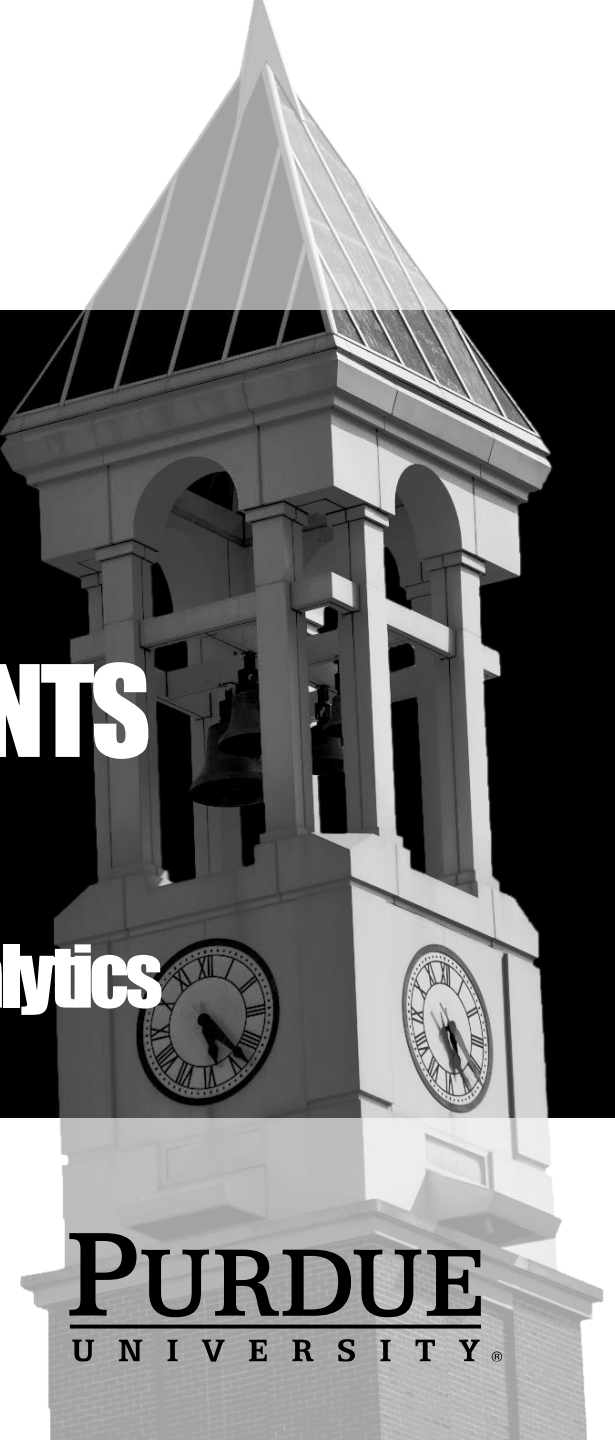
TEACHING ABCS TO BUSINESS STUDENTS

Undergraduate core and Masters in Business Analytics



ALOK CHATURVEDI, ALOK@PURDUE.EDU

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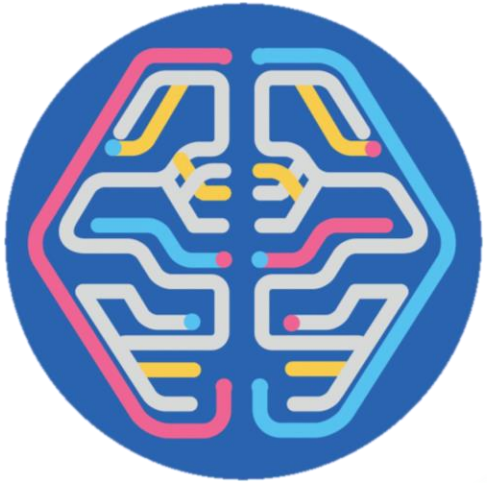
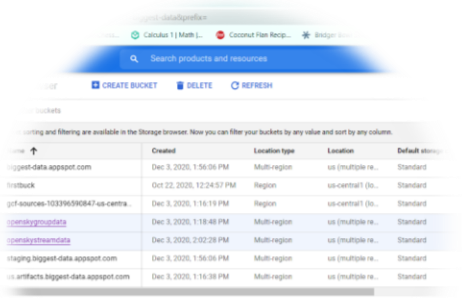
Teaching ABCs

Artificial Intelligence



Graduate BAIM

Big Data



Undergraduate Core

Cloud Computing

Undergraduate MIS core Course (MGMT 382)

- Objectives
  - Inspire students to be **fearless**
  - Overcome **Technophobia**
  - Develop **learning to learn** skills
  - Learn tangible skills that can improve job prospects
    - Google Cloud platform

Cloud Storage

BigQuery

Auto ML

Data Studio

ABC: ML in BigQuery

Create

```
#standardsql
CREATE OR REPLACE MODEL `bts_data.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
  `datapipe-1.bts_data.flights_unpart`
WHERE
  arr_delay IS NOT NULL
```

Evaluate

```
#standardsql
SELECT * FROM ML.EVALUATE(MODEL
`bts_data.ontime`,
(
SELECT
  IF(arr_delay < 15, 1, 0) AS on_time,
  carrier, origin, dest, dep_delay, taxi_out, distance
FROM
  `datapipe-1.bts_data.flights_unpart`
WHERE
  arr_delay IS NOT NULL
))
```

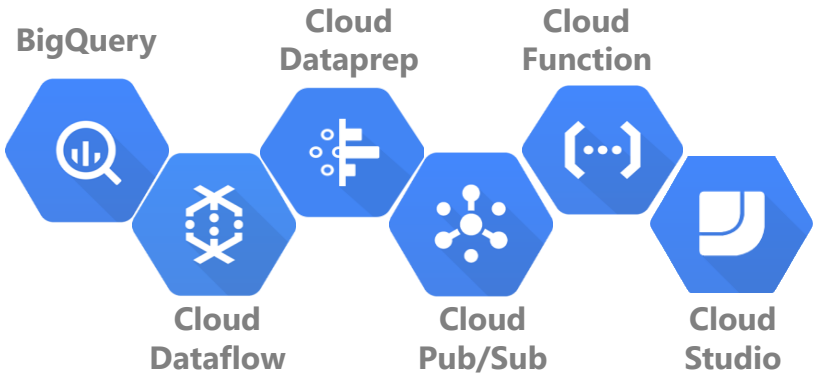
Create

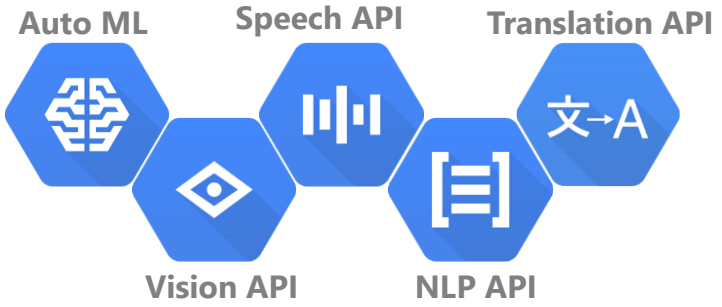
```
SELECT * FROM ml.PREDICT(MODEL `bts_data.ontime`, (
SELECT
  'AA' as carrier,  'DFW' as origin, 'LAX' as dest, dep_delay,
  18 as taxi_out, 1235 as distance
FROM
  UNNEST(GENERATE_ARRAY(-3, 10)) as dep_delay
))
```

Teaching ABCs to U/G core student

MS BAIM Big Data Course (MGMT 590)

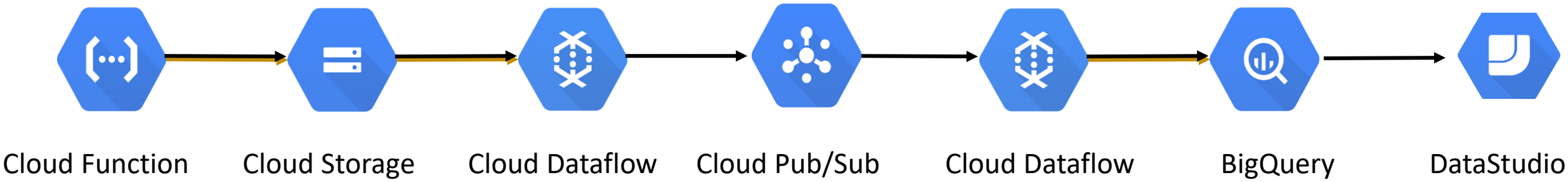
- Objectives
  - Inspire students to be **fearless**
  - Develop **learning to learn** skills
  - Learn to build **end-to-end complex data pipelines**





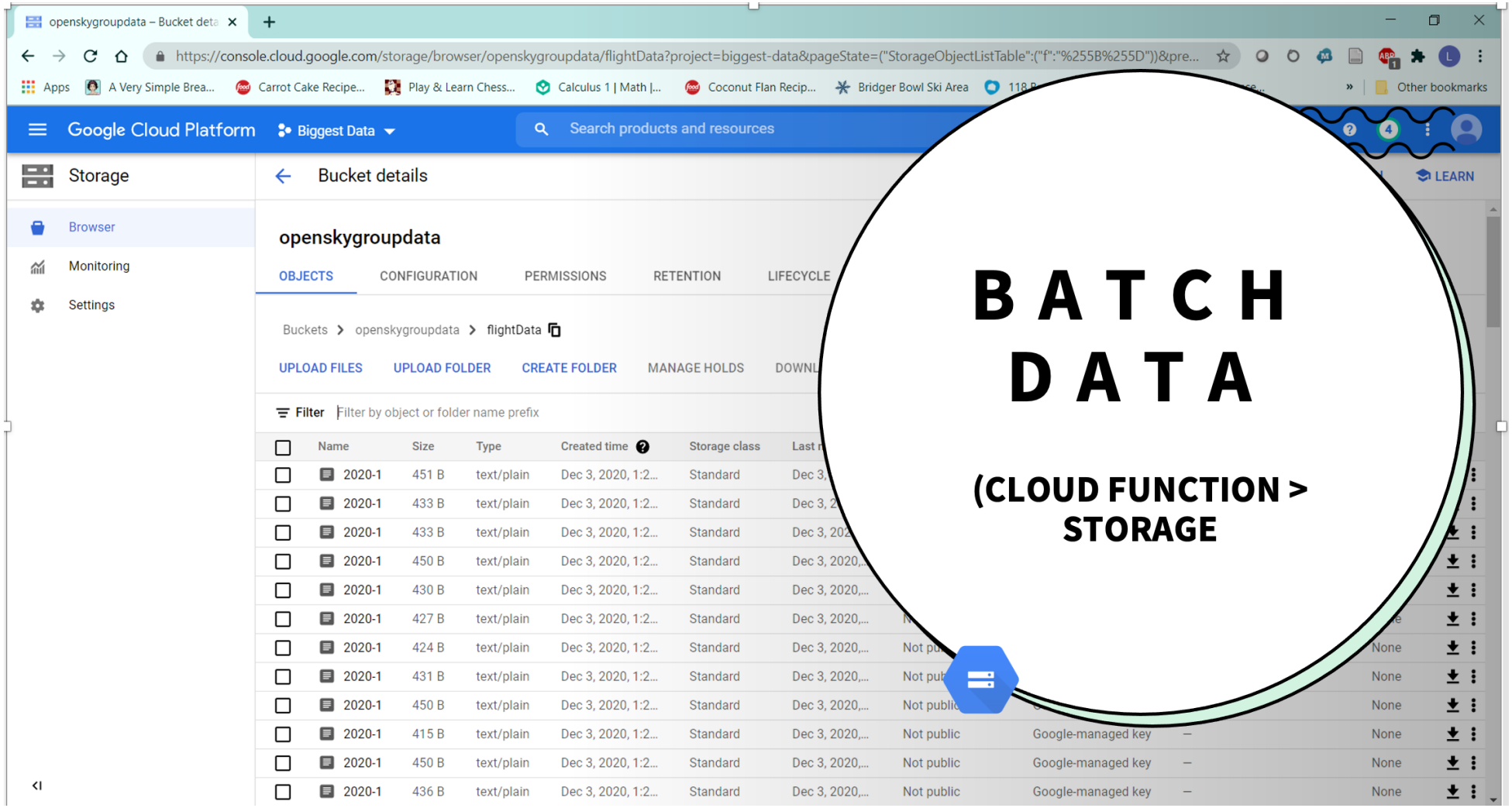
Building Data Pipeline

Batch Data Pipeline



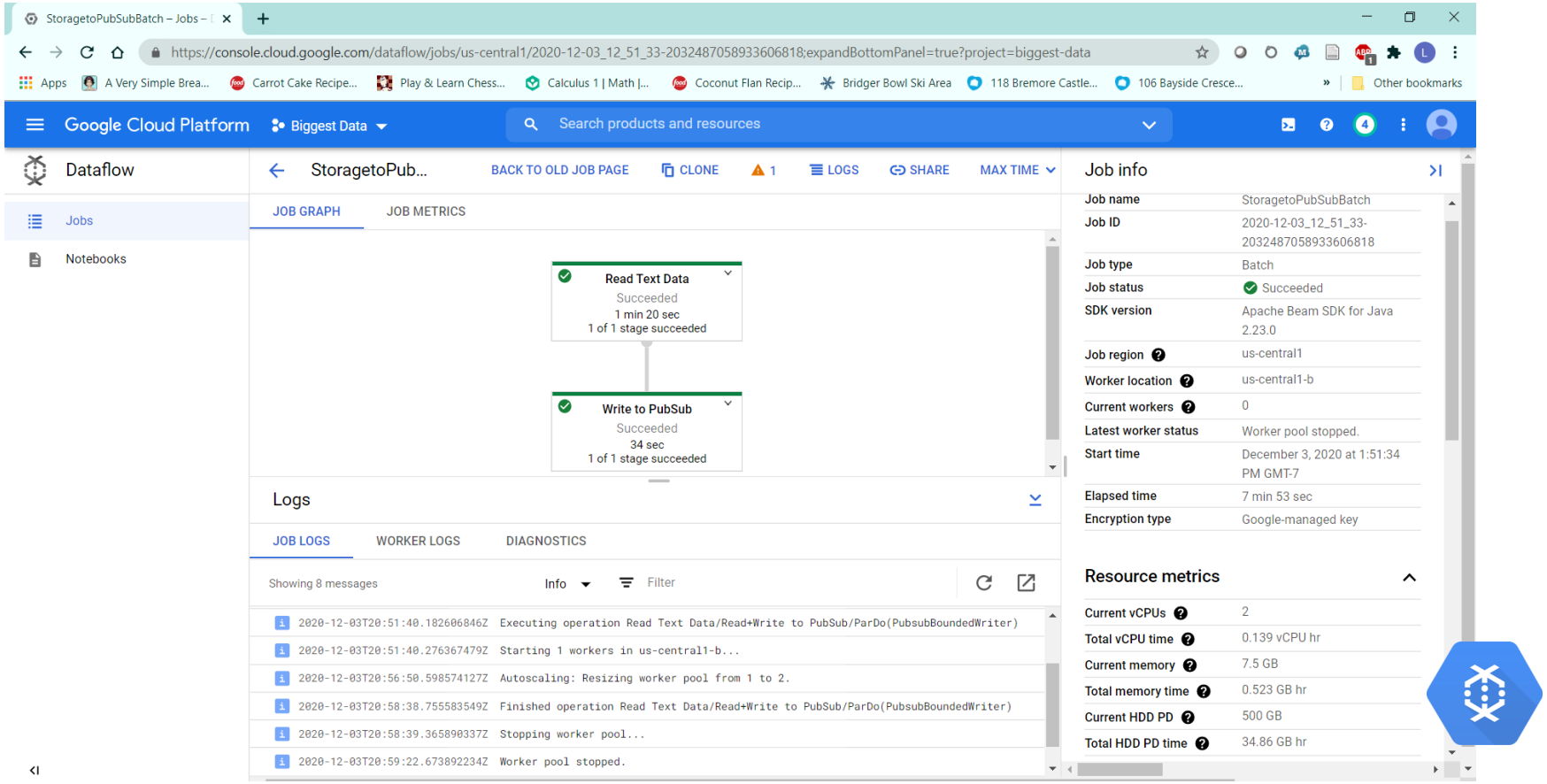
Building Data Pipeline

Batch Data Pipeline



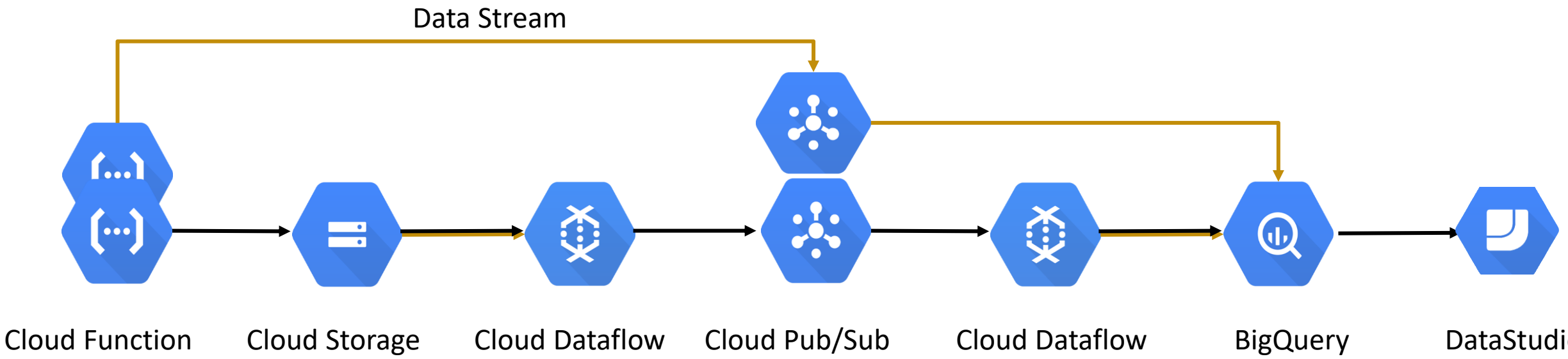
Building Data Pipeline

Batch Data Pipeline



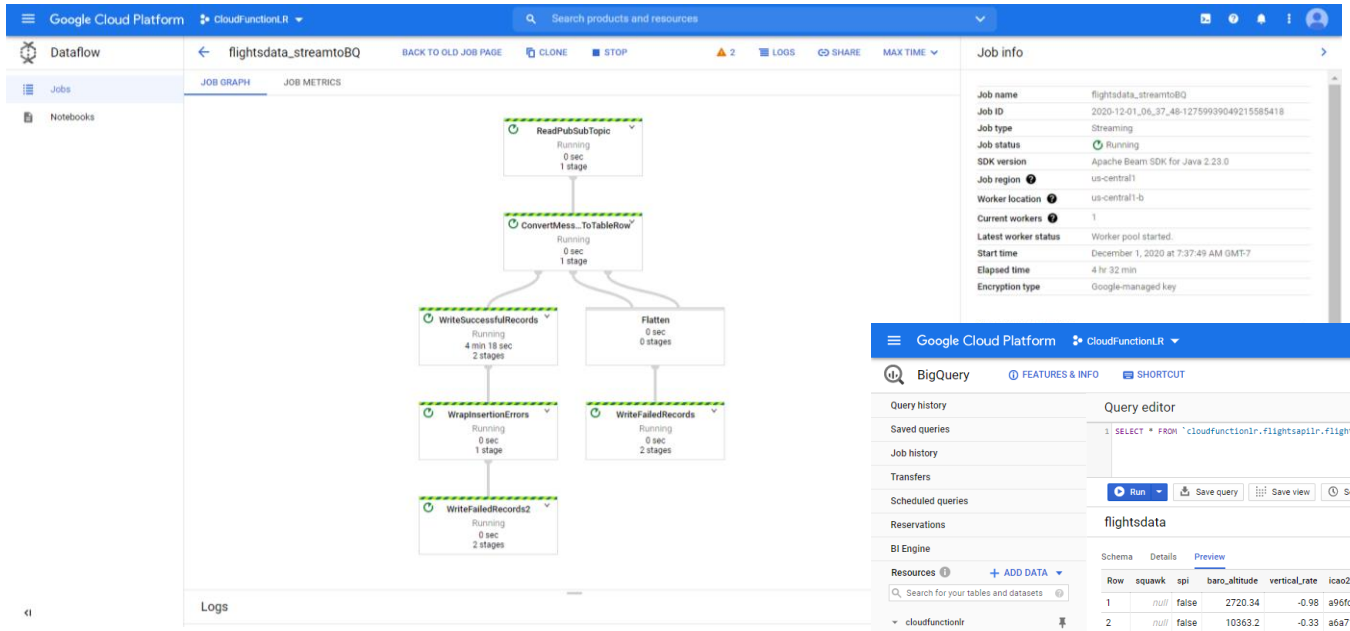
Building Data Pipeline

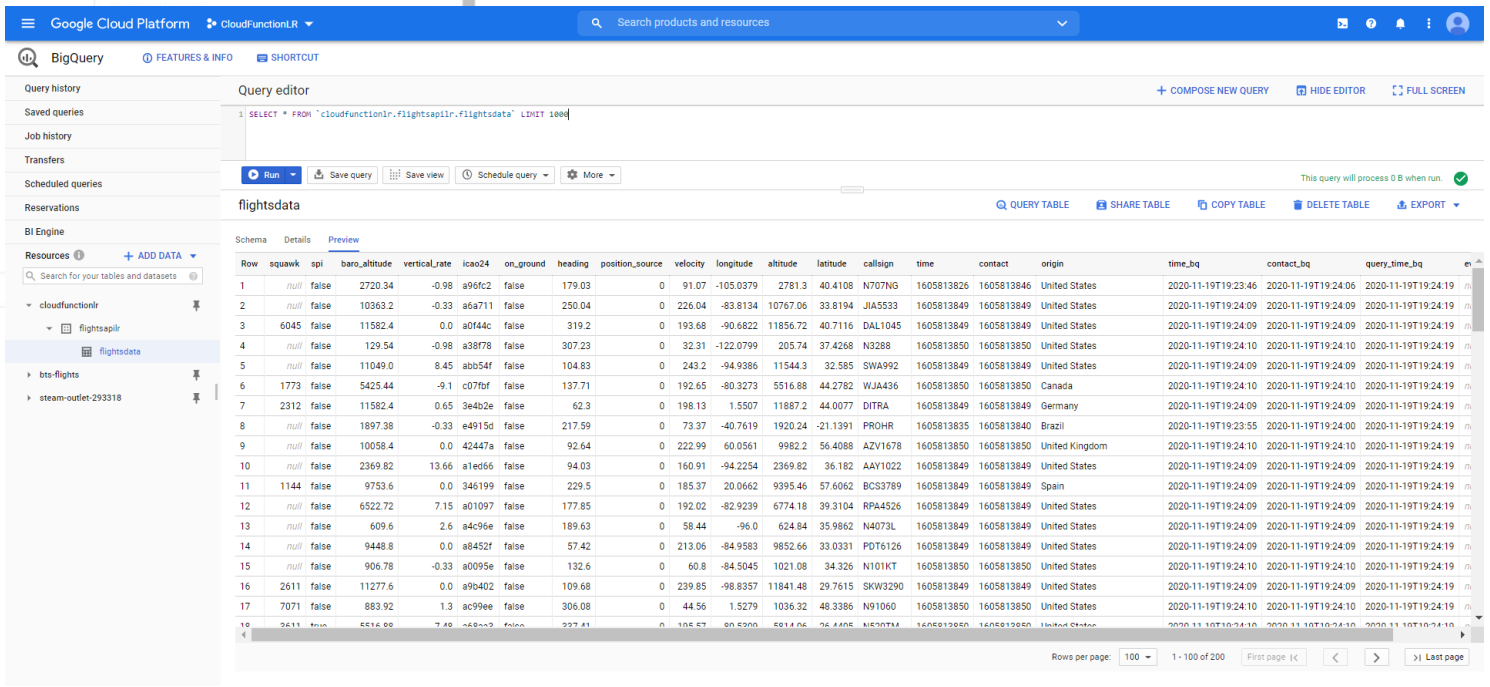
Streaming Data Pipeline



Building Data Pipeline

Streaming Data Pipeline





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11	1144	false	9753.6	0.0	346199	false	229.5	0	185.37	20.0662	9395.46	57.6062	BCS3789	1605813849	1605813849	Spain	2020-11-19T19:24:09	2020-11-19T19:24:09	2020-11-19T19:24:19
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ML ANALYSIS ON BATCH AND STREAMING DATA

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Krannert School of Management

• Big Query: ML Modeling

Question 1: Most major airlines operate across the globe and have agreements with other regional airlines that further extend their reach. Still, each airline has a geographic area that they operate within the most. But which airlines operate in similar spaces?

Question 2: How predictable are itineraries? Can we tell the origin of a flight from the airline, time and day of week?

Before modeling, let's add two fields, one for the Airline code and one for the day of the week, using the following SQL expression:

```
SELECT *, regexp_replace(left(callsign,3),"[0-9]","") AS airline, extract(DAYOFWEEK
from contact_bq) AS weekday
FROM  `flightsapilr.flightsdata`
```

Let's store this as query "fightsdata2"

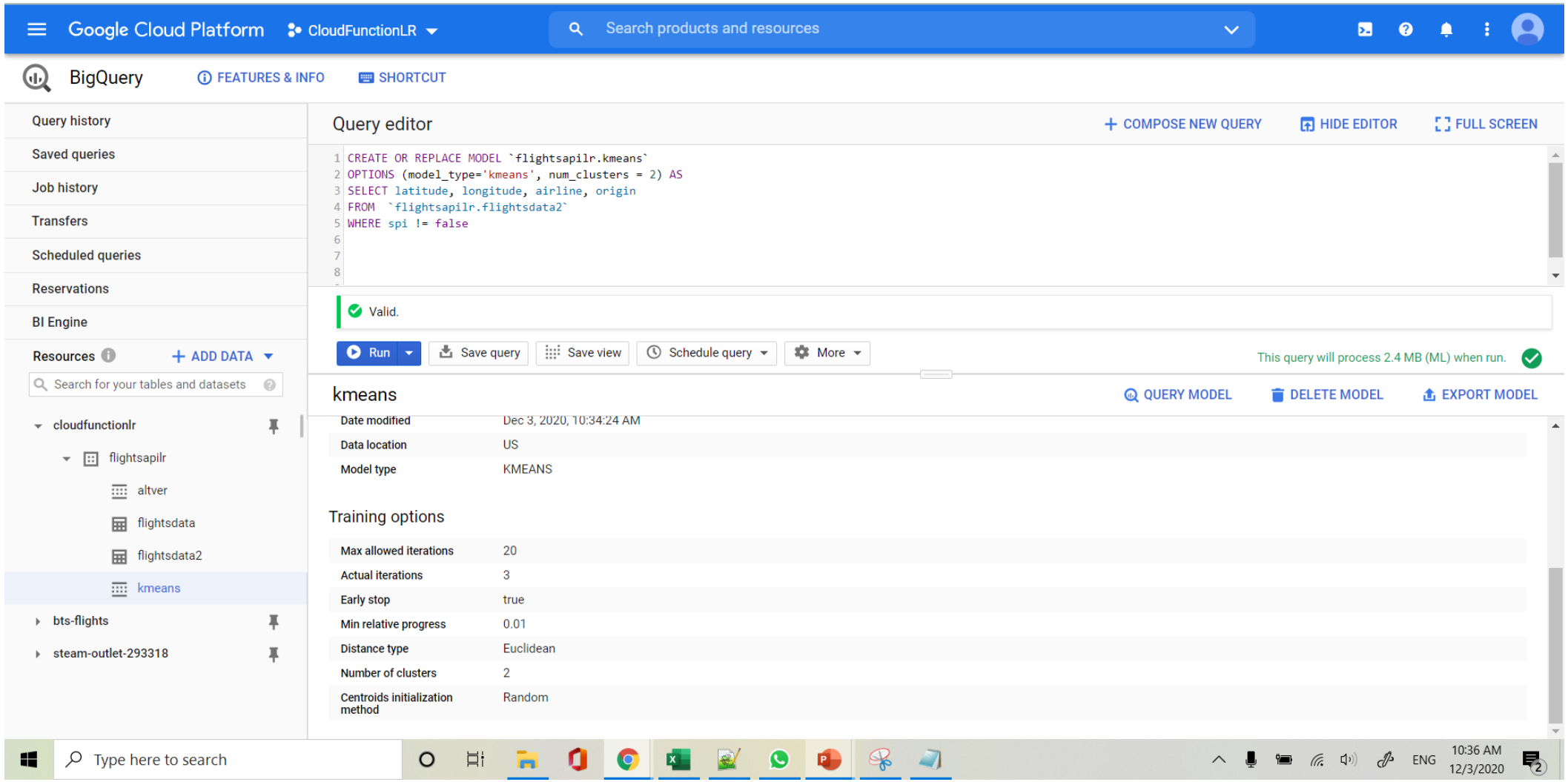
- Big Query: ML Clustering

We can build a k means clustering ML model to answer Question 1:

```
CREATE OR REPLACE MODEL `flightsapilr.kmeans`
OPTIONS (model_type='kmeans', num_clusters = 2) AS
SELECT latitude, longitude, airline, origin
FROM  `flightsapilr.flightsdata2`
WHERE spi != false
```

The number of clusters was selected through iterative trials to minimize the Davies-Bouldin index and MSD and maximize cluster interpretability. The values tried were integers 2 through 7.

Big Query: ML Clustering



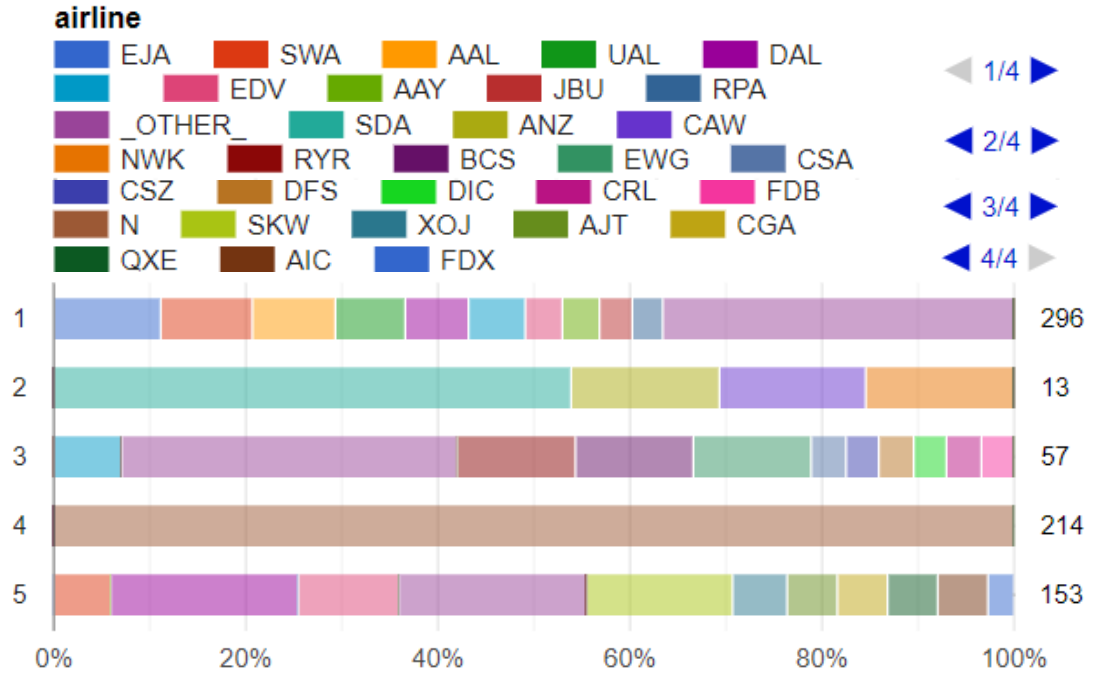
- Big Query: ML Clustering

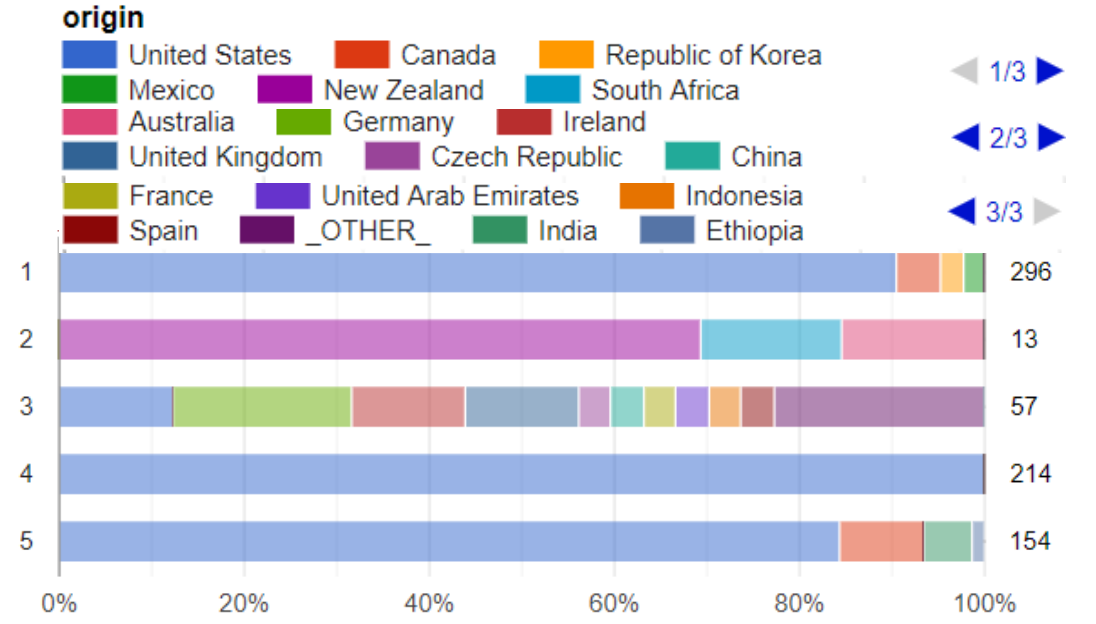
The results from building this model are:

Metrics

Davies–Bouldin index	1.7234
Mean squared distance	1.2103

Centroid Id	Count	latitude	longitude
1	296	35.1396	-92.3316
2	13	-36.9986	143.0028
3	57	41.4898	35.1548
4	214	37.8800	-92.9642
5	154	44.2159	-98.0174





Summary

- Challenge the students
- If you are fearless, students will be fearless
- Focus on learning to learn
- Zoom actually helps in peer-to-peer as you can ask the students to share their screens
- Working with large, real world data helps UG students grow cognitively
- Masters students appreciate what it takes to prepare data before you can use sexy ML models

References

- The Building Blocks of a Modern Data Platform
  - https://towardsdatascience.com/the-building-blocks-of-a-modern-data-platform-92e46061165
- Features in BigQuery's New UI for 2021
  - https://towardsdatascience.com/5-great-features-in-bigquerys-new-ui-for-2021-yes-it-has-tabs-c4bac66d66b
- BigQuery SQL Cheat Sheet
  - https://medium.com/data-school/the-best-bigquery-sql-cheat-sheet-for-beginners-81c762f72845
- BigQuery — Almost All You Need to Know
  - https://medium.com/swlh/bigquery-almost-all-you-need-to-know-f239e6b52279
- Working with Joins, Nested & Repeated Data
  - https://medium.com/google-cloud/bigquery-explained-working-with-joins-nested-repeated-data-1941646ccb5b
- Bigquery ML
  - https://towardsdatascience.com/search?q=Bigquery%20ML