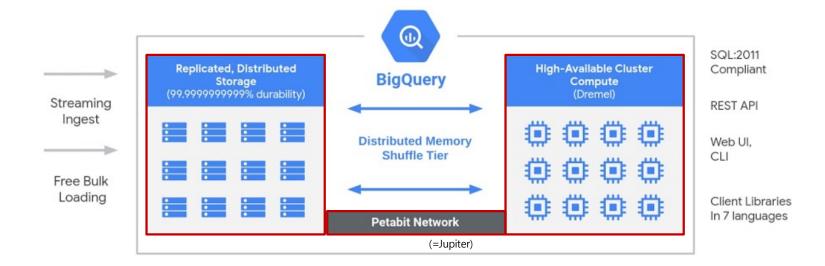
# Term Project Google BigQuery

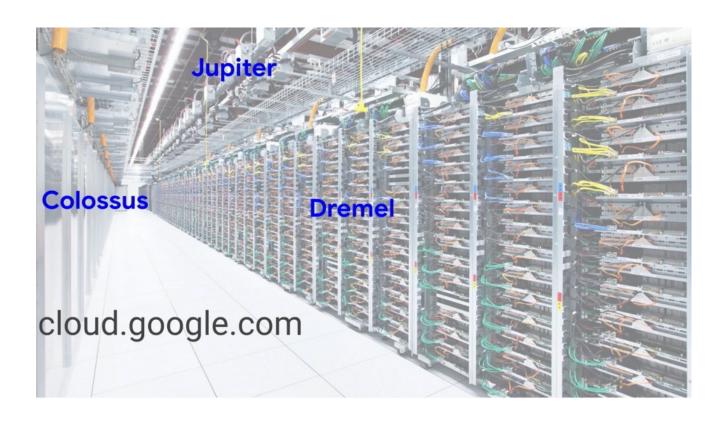
201736055 한지안 201833299 허서윤

- 1. Specs of BigQuery
- 2. Key Features of BigQuery
- 3. Pros and Cons of BigQuery
- 4. Implementation of BigQuery
- 5. References

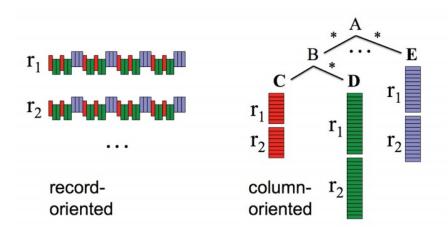


Serverless cloud service for users outside Google based on the Dremel project



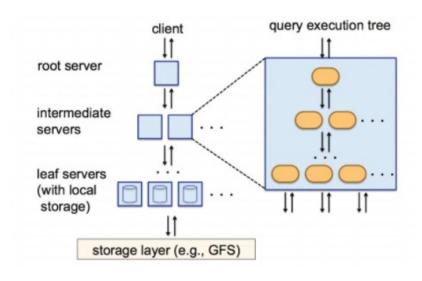


# **1** Columnar Storage



- Save the table in an optimized column format
- Same data type data are gathered and stored
- Each table is compressed and encrypted on a disk
- Storage is durable, and each table replicates between data centers

#### **②** Tree Architecture Distribution



- ☐ Root server
  - Receives SQL query from the user
  - Splits it into a small SQL query
- ☐ Intermediate server
  - -Query split and sent to leaf node (=slot)
  - -Gets through columnar storage process.
- ☐ Leaf server
  - Reads data from a storage layer
  - Delivers results to the parent node.

# **Key Features**

# ① Serverless

Usually, there is no server, and computer resources are used only for analysis Only need to pay at this time.

| ==== | 00 |
|------|----|
|      | 00 |
| ==== | 00 |

# ② Cloud

No need to install/operate as a service. Large capacity support, fast performance support, low price



# **Key Features**

# **3** Stability

The risk of data loss is low because three copies are distributed and stored in different data centers



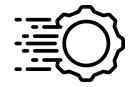
# 4 Batch & Streaming

It provides a batch that loads data at once, and a streaming function that allows you to input data in real time.



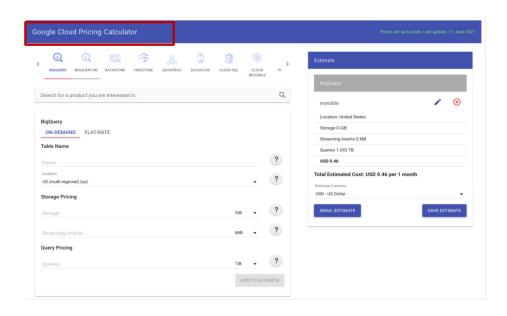
# **5** Dermel project

Structured data can be distributed and analyzed quickly



# **Pros of BigQuery**

1 Cost-effective because it is possible to estimate query costs

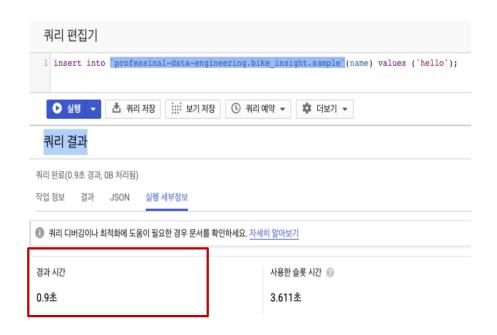


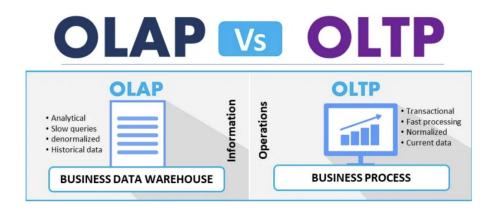
② Models can be created & tested using SQL queries



# **Cons of BigQuery**

# Specialized in analysis and OLAP Not suitable for OLTP





# Establishing and Using Classification Model in Census Data



# **US Census Data**

United States Census Bureau

2000 and 2010 US Census data

#### **Data Information**

Age

Workclass

Marital\_Status,

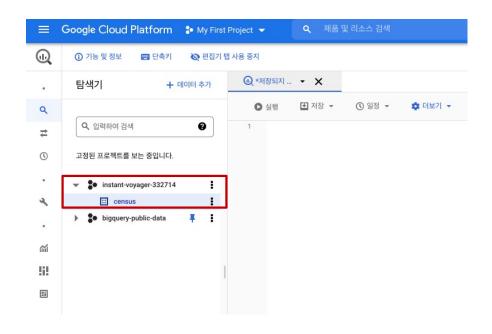
Education\_num

Occupation

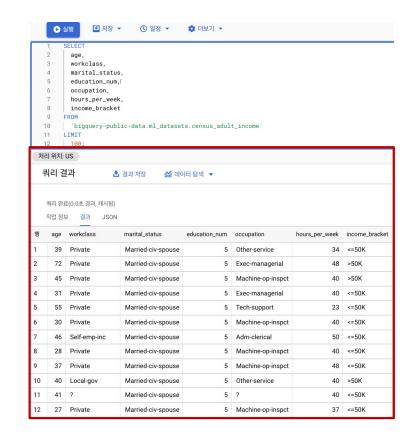
Hours\_per\_week

Income\_bracket

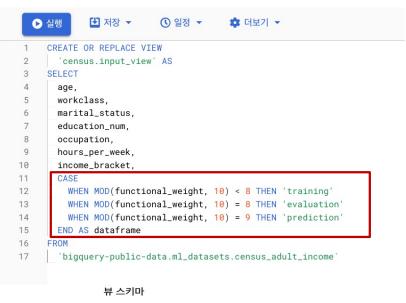
1. Big query data sets are created to store models.



#### 2. Returns 100 rows from a dataset



#### 3. Create a view to compile training data

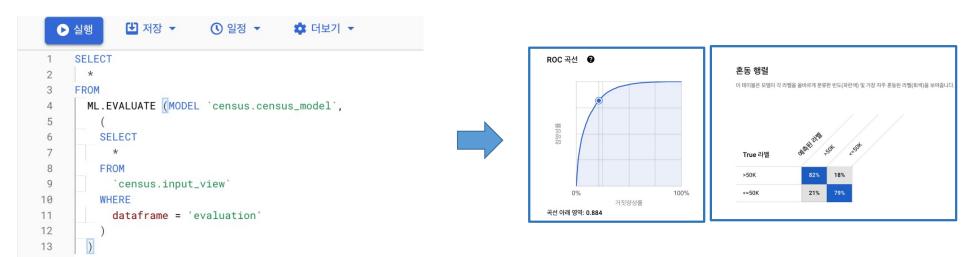


#### ┳ 필터 속성 이름 또는 값 입력 모드 필드 이름 INTEGER NULLABLE age workclass STRING NULLABLE marital\_status STRING NULLABLE INTEGER NULLABLE STRING NULLABLE INTEGER NULLABLE hours\_per\_week income bracket STRING NULLABLE dataframe STRING NULLABLE

#### 4. Create a logistic regression model

```
☑ 저장 ▼
                          ⑤ 일정 ▼
                                        ☆ 더보기 ▼
  ▶ 실행
     CREATE OR REPLACE MODEL
        census.census_model
     OPTIONS
       ( model_type='LOGISTIC_REG',
         auto_class_weights=TRUE,
         input_label_cols=['income_bracket']
       ) AS
     SELECT
       * EXCEPT(dataframe)
     FROM
10
11
        `census.input_view`
12
     WHERE
13
       dataframe = 'training'
```

# 5. Use the ML.EVALUATE function to evaluate the performance of the model





#### 6. Predict the income class of all respondents



# 7. More detailed analysis with Explainable AI method



| 행 | predicted_income_bracket | predicted_income_bracket_probs.label | predicted_income_bracket_probs.prob | age                  | workclass | marital_status     | education_num | occupation | hours_per_week | income_bracket | dataframe  |
|---|--------------------------|--------------------------------------|-------------------------------------|----------------------|-----------|--------------------|---------------|------------|----------------|----------------|------------|
| 1 | <=50K                    | >50K                                 | 0.05639289147442344                 | 34                   | ?         | Married-civ-spouse | 7             | ?          | 8              | <=50K          | prediction |
|   |                          | <=50K                                | 0.9436071085255766                  |                      |           |                    |               |            |                |                |            |
| 2 | <=50K                    | >50K                                 | 0.1311398392666556                  | 311398392666556 21 ? |           | Married-civ-spouse | 9             | ?          | 30             | <=50K          | prediction |
|   |                          | <=50K                                | 0.8688601607333444                  |                      |           |                    |               |            |                |                |            |
| 3 | <=50K                    | >50K                                 | 0.06491298402568849                 | 25                   | ?         | Married-civ-spouse | 9             | ?          | 4              | <=50K          | prediction |
|   |                          | <=50K                                | 0.9350870159743115                  |                      |           |                    |               |            |                |                |            |

# 6. Predict the income class of all respondents

```
☑ 저장 ▼
  ▶ 실행
                          ⑤ 일정 ▼
                                       ☆ 더보기 ▼
     SELECT
     FROM
      ML.PREDICT (MODEL `census.census_model`
5
6
         SELECT
8
         FROM
9
            `census.input_view`
10
           dataframe = 'prediction'
11
12
13
```

# 7. More detailed analysis with Explainable AI method



| 행 | predicted_income_bracket | probability        | top_feature_attributions.feature | top_feature_attributions.attribution | baseline_prediction_value | prediction_value    | approximation_error | age | workclass        | marital_status     | education_num | occupation    | hours_per_week | income_bracket | dataframe  |
|---|--------------------------|--------------------|----------------------------------|--------------------------------------|---------------------------|---------------------|---------------------|-----|------------------|--------------------|---------------|---------------|----------------|----------------|------------|
| 1 | >50K                     | 0.5211861694930122 | hours_per_week                   | 2.0131952297565316                   | -0.29878674958313434      | 0.0847954499691751  | 0.0                 | 59  | Private          | Married-civ-spouse | 4             | Other-service | 99             | <=50K          | evaluation |
|   |                          |                    | education_num                    | -1.8421287256458136                  |                           |                     |                     |     |                  |                    |               |               |                |                |            |
|   |                          |                    | occupation                       | -1.2016119213892107                  |                           |                     |                     |     |                  |                    |               |               |                |                |            |
| 2 | >50K                     | 0.5322760998839042 | occupation                       | -1.2016119213892107                  | -0.29878674958313434      | 0.12928417465217856 | 0.0                 | 47  | Self-emp-not-inc | Married-civ-spouse | 9             | Other-service | 75             | <=50K          | evaluation |
|   |                          |                    | hours_per_week                   | 1.1871782572907503                   |                           |                     |                     |     |                  |                    |               |               |                |                |            |
|   |                          |                    | marital_status                   | 0.9439379268252633                   |                           |                     |                     |     |                  |                    |               |               |                |                |            |

#### Reference

#### Specs of BigQuery

https://syujisu.tistory.com/190?category=907377

https://voutu.be/LhksTFvVriU

#### Architecture of BigQuery

https://cloud.google.com/bigguery

https://velog.io/@jch9537/%ED%95%9C-%EC%A4%84-%EC%9A%A9%EC%96%B4%EB%B0%B0%EC%B9%98Batch%EB%9E%80

#### Pros of BigQuery

https://xo.xello.com.au/blog/google-bigguery-5-benefits-cloud-data-warehouse

https://www.quora.com/What-are-the-pros-and-cons-of-using-Google-BigQuery-as-a-database

https://www.xplenty.com/blog/snowflake-vs-bigguery/

#### Cons of BigQuery

https://www3.technologyevaluation.com/solutions/53566/google-bigquery

https://dzone.com/articles/introduction-to-google-bigquery

#### Big Query Implementation

https://cloud.google.com/bigquery-ml/docs/logistic-regression-prediction

#### Data Source Site

https://console.cloud.google.com/marketplace/product/united-states-census-bureau/us-census-data?project=instant-voyager-332714

# Thank You