Ken Kim, March 16, 2023

Version 1.0

# EV Population Data Pipeline Implementation & Demo

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# Overview

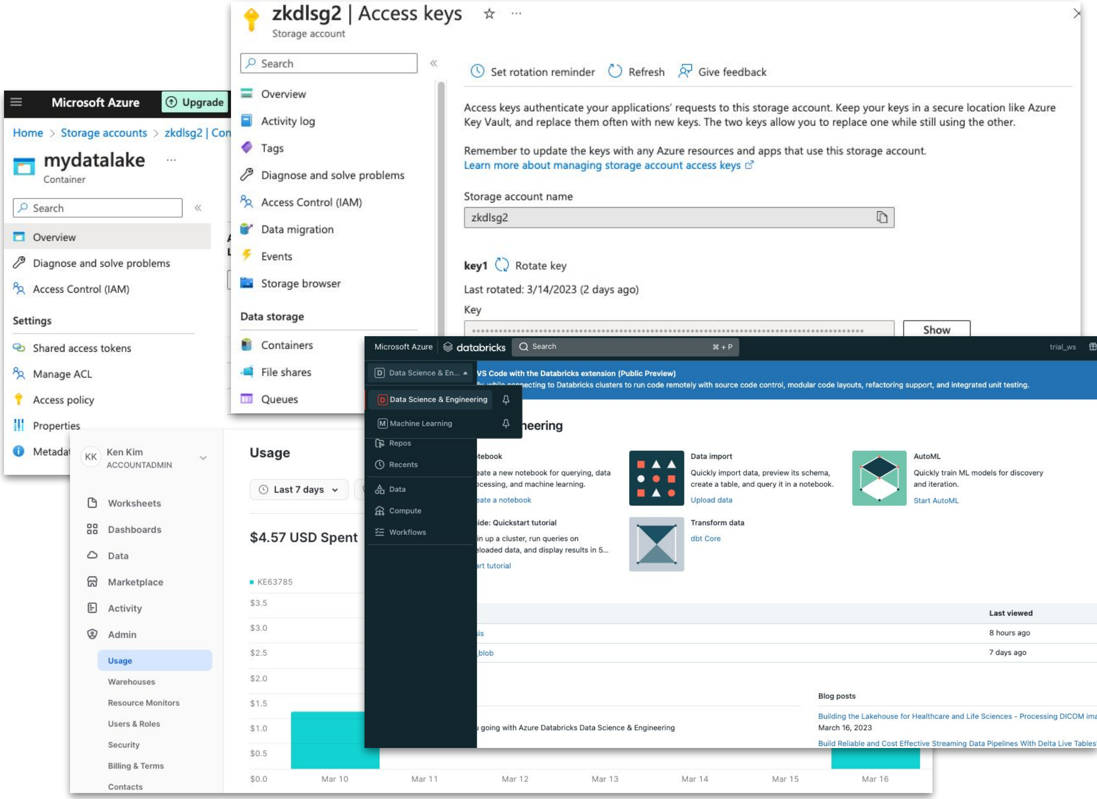
As a part of the interview process for the Snowflake SI Partner Data Cloud Architect role, the hiring team would assess and review  the candidate's technical hands-on skills in Spark, data processing, and data pipeline design.

This assessment requires a demo implementation exercise, which requires the candidate to:
- build a data pipeline that parses the raw data from an Electric Vehicle Population Dataset (provided in a JSON file),
- extract the necessary information, and ingest it into Delta tables and then into DB tables.
- create insightful analysis based on the datasets.

# Preparation

In prior to the code implementation, below are the steps I have prepared as the prerequisite setup and due diligence checks:

- Review of the JSON format and identify the key structures to parse and transform
- Setup Azure env (trial RG) for Storage, Access permission, etc..
- Snowflake trial sign-up
- Databricks trial sign-up
- Etc.



zkdlsg2 | Access keys

Storage account

Access keys authenticate your applications' requests to this storage account. Keep your keys in a secure location like Azure Key Vault, and replace them often with new keys. The two keys allow you to replace one while still using the other.

Remember to update the keys with any Azure resources and apps that use this storage account.

Learn more about managing storage account access keys

Storage account name: zkdlsg2

key1

Last rotated: 3/14/2023 (2 days ago)

Key: ••••••••••••••••••••••••••••••••••••••••••••••••••••••••••••••••••••••••••••••••••••

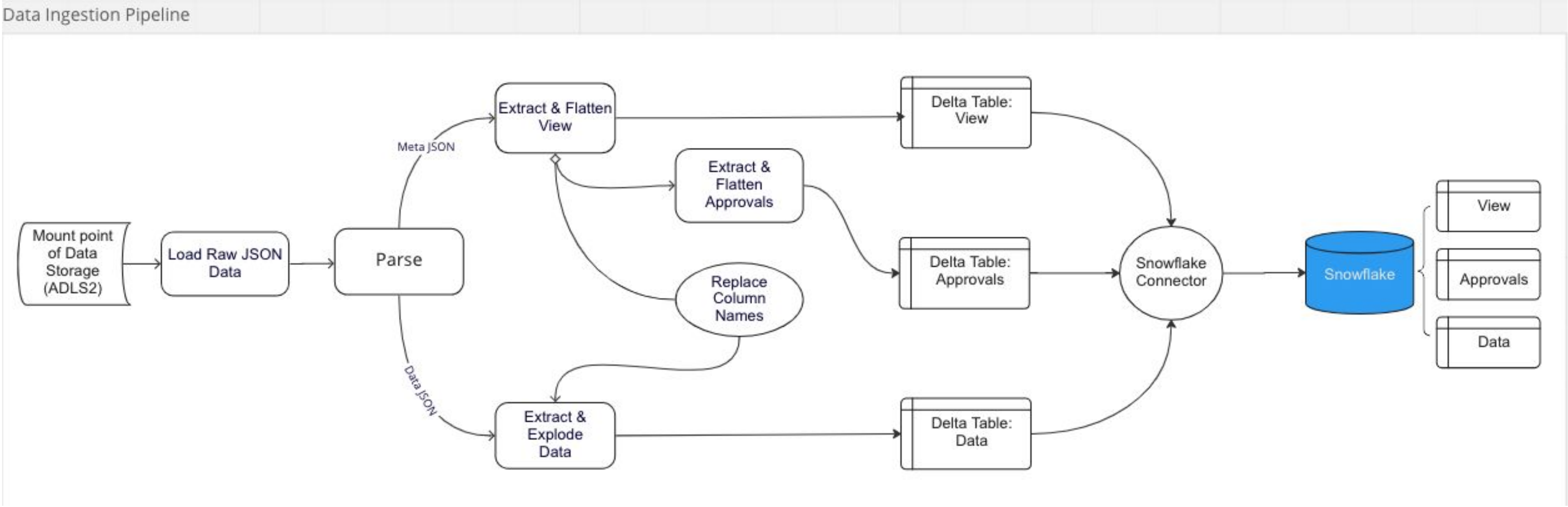
VS Code with the Databricks extension (Public Preview)

...while connecting to Databricks clusters to run code remotely with source code control, modular code layouts, refactoring support, and integrated unit testing.

Usage

$4.57 USD Spent

# Pipeline Architecture



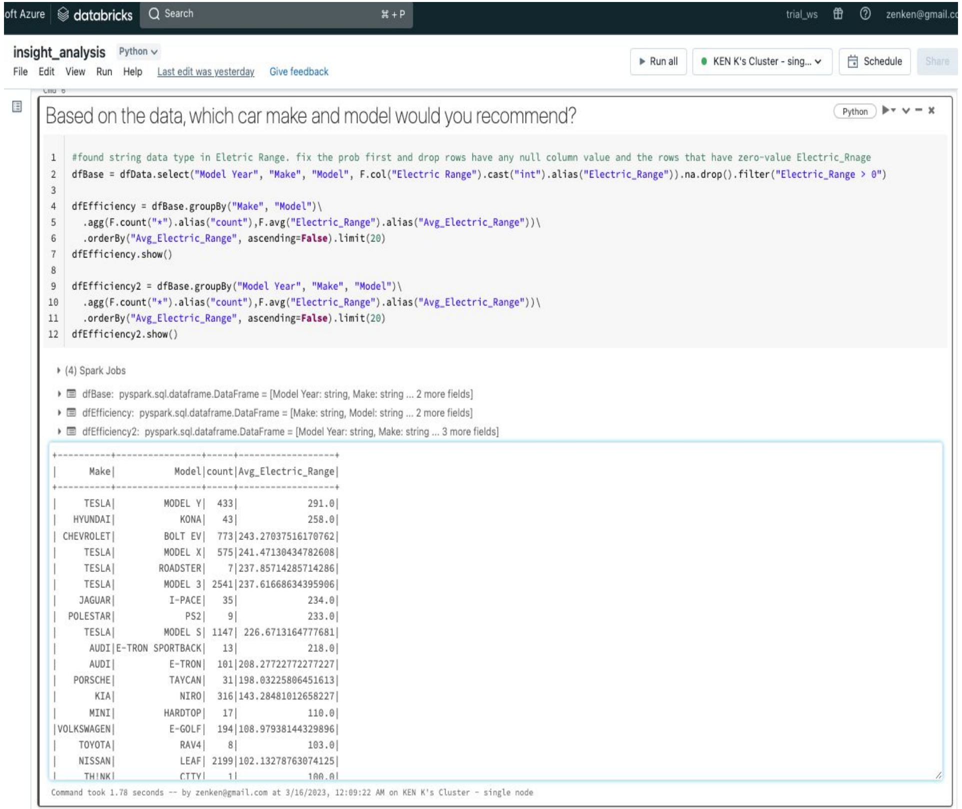
# Demo

## 01: Databricks/Spark

Using Databricks Notebooks, created a Job pipeline which:

- Loads the raw data from ADLS2 storage
- Creates Spark dataframes to parse and extracts JSON objects, meta/view, meta/view/approvals, meta/view/columns and data[]
- Creates Delta Tables to flatten and store the parsed data
- Inserts the same data into Snowflake tables using Snowflake python connector

And  created insights analysis example queries.



Based on the data, which car make and model would you recommend?

```python
#found string data type in Eletric Range. fix the prob first and drop rows have any null column value and the rows that have zero-value Electric_Rnage
dfBase = dfData.select("Model Year", "Make", "Model", F.col("Electric Range").cast("int").alias("Electric_Range")).na.drop().filter("Electric_Range > 0")

dfEfficiency = dfBase.groupBy("Make", "Model")\
  .agg(F.count("*").alias("count"),F.avg("Electric_Range").alias("Avg_Electric_Range"))\
  .orderBy("Avg_Electric_Range", ascending=False).limit(20)
dfEfficiency.show()

dfEfficiency2 = dfBase.groupBy("Model Year", "Make", "Model")\
  .agg(F.count("*").alias("count"),F.avg("Electric_Range").alias("Avg_Electric_Range"))\
  .orderBy("Avg_Electric_Range", ascending=False).limit(20)
dfEfficiency2.show()
```

(4) Spark Jobs

dfBase: pyspark.sql.dataframe.DataFrame = [Model Year: string, Make: string ... 2 more fields]

dfEfficiency: pyspark.sql.dataframe.DataFrame = [Make: string, Model: string ... 2 more fields]

dfEfficiency2: pyspark.sql.dataframe.DataFrame = [Model Year: string, Make: string ... 3 more fields]

```
+----------+----------------+-----+------------------+
|      Make|           Model|count|Avg_Electric_Range|
+----------+----------------+-----+------------------+
|     TESLA|         MODEL Y|  433|             291.0|
|   HYUNDAI|            KONA|   43|             258.0|
| CHEVROLET|         BOLT EV|  773|243.27037516170762|
|     TESLA|         MODEL X|  575|241.47130434782608|
|     TESLA|        ROADSTER|    7|237.85714285714286|
|     TESLA|         MODEL 3| 2541|237.61668634395906|
|    JAGUAR|          I-PACE|   35|             234.0|
|  POLESTAR|             PS2|    9|             233.0|
|     TESLA|         MODEL S| 1147| 226.6713164777681|
|      AUDI|E-TRON SPORTBACK|   13|             218.0|
|      AUDI|          E-TRON|  101|208.27722772277227|
|   PORSCHE|          TAYCAN|   31|198.03225806451613|
|       KIA|            NIRO|  316|143.28481012658227|
|      MINI|         HARDTOP|   17|             110.0|
|VOLKSWAGEN|          E-GOLF|  194|108.97938144329896|
|    TOYOTA|            RAV4|    8|             103.0|
|    NISSAN|            LEAF| 2199|102.13278763074125|
|     TH!NK|            CITY|    1|             100.0|
```

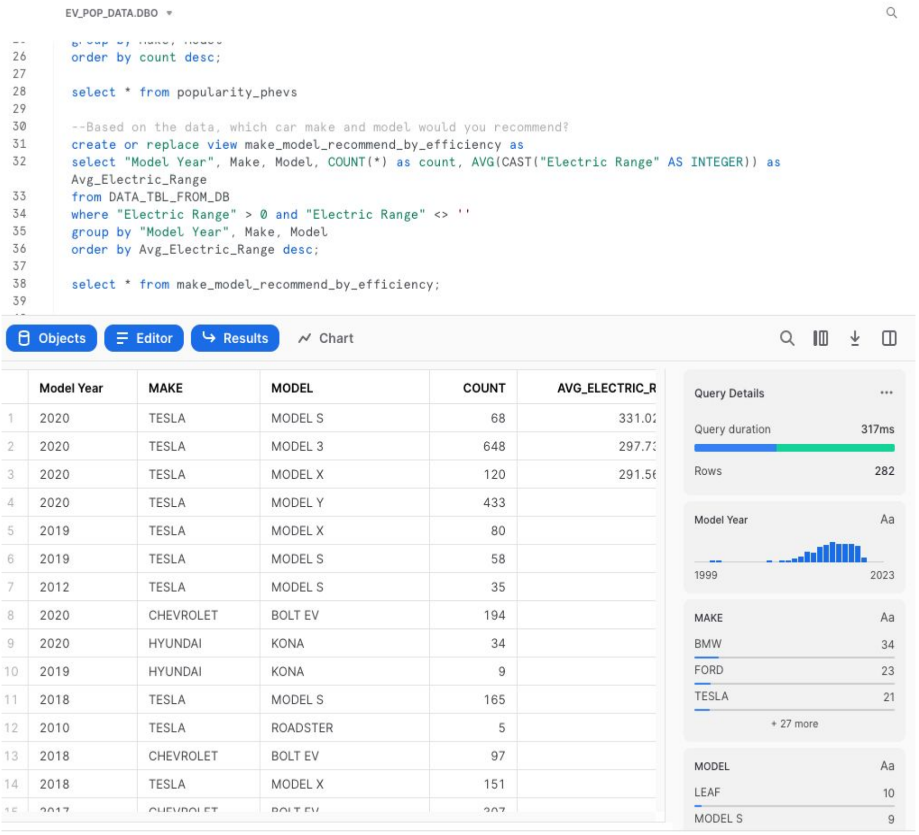
Command took 1.78 seconds -- by zenken@gmail.com at 3/16/2023, 12:09:22 AM on KEN K's Cluster - single node

# Demo
## 02: Snowflake/Snowpark

Having the same extracted data loaded into Snowflake tables, generated view for the same insight analysis queries.

Created a Snowpipe to process the same JSON data ingestion to compare to Databricks Job Workflow.

Used Snowpark API to perform the same Dataframe



```
group by Make, Model
order by count desc;

select * from popularity_phevs

--Based on the data, which car make and model would you recommend?
create or replace view make_model_recommend_by_efficiency as
select "Model Year", Make, Model, COUNT(*) as count, AVG(CAST("Electric Range" AS INTEGER)) as
Avg_Electric_Range
from DATA_TBL_FROM_DB
where "Electric Range" > 0 and "Electric Range" <> ''
group by "Model Year", Make, Model
order by Avg_Electric_Range desc;

select * from make_model_recommend_by_efficiency;
```

| | Model Year | MAKE | MODEL | COUNT | AVG_ELECTRIC_R |
|---|---|---|---|---|---|
| 1 | 2020 | TESLA | MODEL S | 68 | 331.0 |
| 2 | 2020 | TESLA | MODEL 3 | 648 | 297.7 |
| 3 | 2020 | TESLA | MODEL X | 120 | 291.5 |
| 4 | 2020 | TESLA | MODEL Y | 433 | |
| 5 | 2019 | TESLA | MODEL X | 80 | |
| 6 | 2019 | TESLA | MODEL S | 58 | |
| 7 | 2012 | TESLA | MODEL S | 35 | |
| 8 | 2020 | CHEVROLET | BOLT EV | 194 | |
| 9 | 2020 | HYUNDAI | KONA | 34 | |
| 10 | 2019 | HYUNDAI | KONA | 9 | |
| 11 | 2018 | TESLA | MODEL S | 165 | |
| 12 | 2010 | TESLA | ROADSTER | 5 | |
| 13 | 2018 | CHEVROLET | BOLT EV | 97 | |
| 14 | 2018 | TESLA | MODEL X | 151 | |
| 15 | 2017 | CHEVROLET | BOLT EV | 207 | |

Query Details

Query duration 317ms

Rows 282

Model Year Aa

1999 2023

MAKE Aa

| | |
|---|---|
| BMW | 34 |
| FORD | 23 |
| TESLA | 21 |

+ 27 more

MODEL Aa

| | |
|---|---|
| LEAF | 10 |
| MODEL S | 9 |

# Snowpark vs Databricks Spark

Snowpark and Databricks Spark are both powerful tools for data processing and analysis. However, there are several benefits to using Snowpark over Databricks Spark:

**Performance**: Snowpark is designed to optimize performance for Snowflake's data warehouse environment. This means that Snowpark jobs can run faster and more efficiently than Databricks Spark jobs when working with Snowflake.

**Integration with Snowflake**: Snowpark is tightly integrated with Snowflake, which makes it easy to write Spark code that can interact with Snowflake data warehouses. This means that you can use Snowpark to load data into Snowflake, extract data from Snowflake, and run complex analytical queries on Snowflake data.

**Flexibility**: Snowpark is a more flexible tool than Databricks Spark, as it can be used in a variety of environments, including on-premises data centers and public clouds. This means that you can use Snowpark to build data processing pipelines that meet your specific business needs, regardless of your organization's IT infrastructure.

Overall, Snowpark offers several benefits over Databricks Spark when working with Snowflake data warehouses. If your organization is already using Snowflake and needs a high-performance, flexible tool for data processing and analysis, Snowpark is definitely worth considering.

# Thank you.