### Taller

### Procesamiento Distribuido en la Nube

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Configuracion inicial antes de correr Spark

En un terminal, de SageMaker, se debe correr los siguientes comandos para garantizar que se tiene la configuracion adecuada de librerias

In [1]:
```
import os
os.environ["SPARK_VERSION"] = '3.3'
os.environ["JAVA_HOME"] = '/usr/lib/jvm/java-11-openjdk-amd64/'
```

**Instalacion de Librerias**

In [2]:
```
!pip install pydeequ==1.2.0
!pip install pyspark
!pip install sagemaker_pyspark
!pip install seaborn
```

```
Collecting pydeequ==1.2.0
  Downloading pydeequ-1.2.0-py3-none-any.whl.metadata (9.1 kB)
Requirement already satisfied: numpy>=1.14.1 in /usr/local/lib/python3.10/dist-packages
(from pydeequ==1.2.0) (1.26.4)
Requirement already satisfied: pandas>=0.23.0 in /usr/local/lib/python3.10/dist-packages
(from pydeequ==1.2.0) (2.1.4)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/dist-
packages (from pandas>=0.23.0->pydeequ==1.2.0) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages
(from pandas>=0.23.0->pydeequ==1.2.0) (2024.2)
Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-packages
(from pandas>=0.23.0->pydeequ==1.2.0) (2024.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from
python-dateutil>=2.8.2->pandas>=0.23.0->pydeequ==1.2.0) (1.16.0)
Downloading pydeequ-1.2.0-py3-none-any.whl (37 kB)
Installing collected packages: pydeequ
Successfully installed pydeequ-1.2.0
Collecting pyspark
  Downloading pyspark-3.5.2.tar.gz (317.3 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 317.3/317.3 MB
3.9 MB/s eta 0:00:00
  Preparing metadata (setup.py) ... done
Requirement already satisfied: py4j==0.10.9.7 in /usr/local/lib/python3.10/dist-packages
 (from pyspark) (0.10.9.7)
Building wheels for collected packages: pyspark
  Building wheel for pyspark (setup.py) ... done
  Created wheel for pyspark: filename=pyspark-3.5.2-py2.py3-none-any.whl size=317812365
 sha256=6ef8f8d3b538dc8fcc89ab01383dd667f46f98c9dbb4f7859b71f19784859880
  Stored in directory: /root/.cache/pip/wheels/34/34/bd/03944534c44b677cd5859f248090daa9
fb27b3c8f8e5f49574
Successfully built pyspark
Installing collected packages: pyspark
Successfully installed pyspark-3.5.2
Collecting sagemaker_pyspark
  Downloading sagemaker_pyspark-1.4.5.tar.gz (181.5 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 181.5/181.5 MB
6.4 MB/s eta 0:00:00
  Preparing metadata (setup.py) ... done
Collecting pyspark==3.3.0 (from sagemaker_pyspark)
```

```
  Downloading pyspark-3.3.0.tar.gz (281.3 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 281.3/281.3 MB
4.6 MB/s eta 0:00:00
  Preparing metadata (setup.py) ... done
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from sa
gemaker_pyspark) (1.26.4)
Collecting py4j==0.10.9.5 (from pyspark==3.3.0->sagemaker_pyspark)
  Downloading py4j-0.10.9.5-py2.py3-none-any.whl.metadata (1.5 kB)
Downloading py4j-0.10.9.5-py2.py3-none-any.whl (199 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 199.7/199.7 kB 1
0.8 MB/s eta 0:00:00
Building wheels for collected packages: sagemaker_pyspark, pyspark
  Building wheel for sagemaker_pyspark (setup.py) ... done
  Created wheel for sagemaker_pyspark: filename=sagemaker_pyspark-1.4.5-py3-none-any.whl
 size=181610593 sha256=fedda2af44ae2db0657bdeb35dcbddfdbdb255b63ad30a31e1076da4ed6cf99d
  Stored in directory: /root/.cache/pip/wheels/ea/cb/32/140bffbc4ad8465e99b41cd848723a28
7b07650044483c62fa
  Building wheel for pyspark (setup.py) ... done
  Created wheel for pyspark: filename=pyspark-3.3.0-py2.py3-none-any.whl size=281764003
 sha256=79be9471864b76c6b2f55107b3e51ad001162673d24e21390ea43848bc1fd274
  Stored in directory: /root/.cache/pip/wheels/81/9c/6c/d5200fcf351ffa39cbe09911e9970328
3624cd037df58070d9
Successfully built sagemaker_pyspark pyspark
Installing collected packages: py4j, pyspark, sagemaker_pyspark
  Attempting uninstall: py4j
    Found existing installation: py4j 0.10.9.7
    Uninstalling py4j-0.10.9.7:
      Successfully uninstalled py4j-0.10.9.7
  Attempting uninstall: pyspark
    Found existing installation: pyspark 3.5.2
    Uninstalling pyspark-3.5.2:
      Successfully uninstalled pyspark-3.5.2
Successfully installed py4j-0.10.9.5 pyspark-3.3.0 sagemaker_pyspark-1.4.5
Requirement already satisfied: seaborn in /usr/local/lib/python3.10/dist-packages (0.13.
1)
Requirement already satisfied: numpy!=1.24.0,>=1.20 in /usr/local/lib/python3.10/dist-pa
ckages (from seaborn) (1.26.4)
Requirement already satisfied: pandas>=1.2 in /usr/local/lib/python3.10/dist-packages (f
rom seaborn) (2.1.4)
Requirement already satisfied: matplotlib!=3.6.1,>=3.4 in /usr/local/lib/python3.10/dist
-packages (from seaborn) (3.7.1)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packag
es (from matplotlib!=3.6.1,>=3.4->seaborn) (1.3.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages
 (from matplotlib!=3.6.1,>=3.4->seaborn) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packa
ges (from matplotlib!=3.6.1,>=3.4->seaborn) (4.53.1)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packa
ges (from matplotlib!=3.6.1,>=3.4->seaborn) (1.4.7)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-package
s (from matplotlib!=3.6.1,>=3.4->seaborn) (24.1)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages
 (from matplotlib!=3.6.1,>=3.4->seaborn) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packag
es (from matplotlib!=3.6.1,>=3.4->seaborn) (3.1.4)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-pa
ckages (from matplotlib!=3.6.1,>=3.4->seaborn) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages
 (from pandas>=1.2->seaborn) (2024.2)
Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-packages
 (from pandas>=1.2->seaborn) (2024.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from
 python-dateutil>=2.7->matplotlib!=3.6.1,>=3.4->seaborn) (1.16.0)
```

### Uso de Librerias

In [3]:
```
import pyspark
import sagemaker_pyspark
import pydeequ
```

In [143…
```
from pyspark.sql import SparkSession, Row, DataFrame
import pandas as pd
import sagemaker_pyspark

from pyspark.sql.types import *
from pyspark.sql.functions import *
from pyspark.sql.functions import col, sum as spark_sum

import pydeequ
from pydeequ.repository import *
from pydeequ.analyzers import *
from pydeequ.verification import *
from pydeequ.anomaly_detection import *
from pydeequ.analyzers import *

from pydeequ.profiles import *

import matplotlib.pyplot as plt
import seaborn as sns
import folium
```

**Creacion de la sesion de Spark**

Utilizando las configuraciones de paquete maven

In [5]:
```
classpath = ":".join(sagemaker_pyspark.classpath_jars())

spark = (SparkSession
    .builder
    .config("spark.driver.extraClassPath", classpath)
    .config("spark.jars.packages", pydeequ.deequ_maven_coord)
    .config("spark.jars.excludes", pydeequ.f2j_maven_coord)
    .getOrCreate())
```

In [6]:
```
# Programmatic way to define a schema
tesla_schema = StructType([StructField('VIN', StringType(), True),
 StructField('County', StringType(), True),
 StructField('City', StringType(), True),#IntegerType
 StructField('State', StringType(), True),
 StructField('Postal_Code', IntegerType(), True),
 StructField('Model_Year', IntegerType(), True),
 StructField('Make', StringType(), True),
 StructField('Model', StringType(), True),
 StructField('Electric_Vehicle_Type', StringType(), True),
 StructField('CAFV', StringType(), True),
 StructField('Electric_Range', IntegerType(), True),
 StructField('Base_MSRP', IntegerType(), True),
 StructField('Legislative_District', IntegerType(), True),
 StructField('DOL_Vehicle_ID', IntegerType(), True),
 StructField('Vehicle_Location', StringType(), True),
 StructField('Electric_Utility', StringType(), True),
 StructField('2020_Census_Tract', LongType(), True)])
```

In [8]:
```
#csv_url = "https://raw.githubusercontent.com/carlosjara/MCD_PDN/main/Clase_3_StepFuncti
#falla al traerlo de git, cargar "manualmente"
# df = spark.read.csv("data/Electric_Vehicle_Population_Data.csv", header=True,schema=te
df = spark.read.csv("Electric_Vehicle_Population_Data.csv", header=True,schema=tesla_sch
```

In [9]:
```python
print(df.printSchema())
```

```
root
 |-- VIN: string (nullable = true)
 |-- County: string (nullable = true)
 |-- City: string (nullable = true)
 |-- State: string (nullable = true)
 |-- Postal_Code: integer (nullable = true)
 |-- Model_Year: integer (nullable = true)
 |-- Make: string (nullable = true)
 |-- Model: string (nullable = true)
 |-- Electric_Vehicle_Type: string (nullable = true)
 |-- CAFV: string (nullable = true)
 |-- Electric_Range: integer (nullable = true)
 |-- Base_MSRP: integer (nullable = true)
 |-- Legislative_District: integer (nullable = true)
 |-- DOL_Vehicle_ID: integer (nullable = true)
 |-- Vehicle_Location: string (nullable = true)
 |-- Electric_Utility: string (nullable = true)
 |-- 2020_Census_Tract: long (nullable = true)

None
```

In [15]:
```python
display(df.head(5))
```

```
[Row(VIN='5YJ3E1EB0J', County='Thurston', City='Olympia', State='WA', Postal_Code=98512,
Model_Year=2018, Make='TESLA', Model='MODEL 3', Electric_Vehicle_Type='Battery Electric
Vehicle (BEV)', CAFV='Clean Alternative Fuel Vehicle Eligible', Electric_Range=215, Base
_MSRP=0, Legislative_District=35, DOL_Vehicle_ID=104823078, Vehicle_Location='POINT (-12
2.957046 46.991391)', Electric_Utility='PUGET SOUND ENERGY INC', 2020_Census_Tract=53067
012730),
 Row(VIN='WA1AAAGE9M', County='Kitsap', City='Port Orchard', State='WA', Postal_Code=983
67, Model_Year=2021, Make='AUDI', Model='E-TRON', Electric_Vehicle_Type='Battery Electri
c Vehicle (BEV)', CAFV='Clean Alternative Fuel Vehicle Eligible', Electric_Range=222, Ba
se_MSRP=0, Legislative_District=35, DOL_Vehicle_ID=156660507, Vehicle_Location='POINT (-
122.6530052 47.4739066)', Electric_Utility='PUGET SOUND ENERGY INC', 2020_Census_Tract=5
3035092901),
 Row(VIN='5YJ3E1EA2J', County='Yakima', City='Yakima', State='WA', Postal_Code=98902, Mo
del_Year=2018, Make='TESLA', Model='MODEL 3', Electric_Vehicle_Type='Battery Electric Ve
hicle (BEV)', CAFV='Clean Alternative Fuel Vehicle Eligible', Electric_Range=215, Base_M
SRP=0, Legislative_District=14, DOL_Vehicle_ID=269374108, Vehicle_Location='POINT (-120.
530331 46.59534)', Electric_Utility='PACIFICORP', 2020_Census_Tract=53077000500),
 Row(VIN='5YJ3E1EA4N', County='Yakima', City='Yakima', State='WA', Postal_Code=98902, Mo
del_Year=2022, Make='TESLA', Model='MODEL 3', Electric_Vehicle_Type='Battery Electric Ve
hicle (BEV)', CAFV='Eligibility unknown as battery range has not been researched', Elect
ric_Range=0, Base_MSRP=0, Legislative_District=15, DOL_Vehicle_ID=213383894, Vehicle_Loc
ation='POINT (-120.530331 46.59534)', Electric_Utility='PACIFICORP', 2020_Census_Tract=5
3077001202),
 Row(VIN='7SAYGAEE2P', County='Snohomish', City='Bothell', State='WA', Postal_Code=9801
2, Model_Year=2023, Make='TESLA', Model='MODEL Y', Electric_Vehicle_Type='Battery Electr
ic Vehicle (BEV)', CAFV='Eligibility unknown as battery range has not been researched',
Electric_Range=0, Base_MSRP=0, Legislative_District=1, DOL_Vehicle_ID=229496046, Vehicle
_Location='POINT (-122.206146 47.839957)', Electric_Utility='PUGET SOUND ENERGY INC', 20
20_Census_Tract=53061052009)]
```

In [11]:
```python
# Contar nulos por columna
df.select([spark_sum(col(c).isNull().cast("int")).alias(c) for c in df.columns]).show()
```

```
+---+------+----+-----+-----------+----------+----+-----+---------------------+----+----
----------+---------+--------------------+--------------+----------------+--------------
--+-----------------+
|VIN|County|City|State|Postal_Code|Model_Year|Make|Model|Electric_Vehicle_Type|CAFV|Elec
tric_Range|Base_MSRP|Legislative_District|DOL_Vehicle_ID|Vehicle_Location|Electric_Utili
ty|2020_Census_Tract|
+---+------+----+-----+-----------+----------+----+-----+---------------------+----+----
----------+---------+--------------------+--------------+----------------+--------------
```

```
--+-----------------+
|  0|     4|   4|    0|          4|          0|    0|     0|                     0|    0|
         0|         0|                    442|               0|                8|
4|                 4|
+---+------+----+-----+-----------+----------+----+-----+---------------------+----+----
----------+---------+--------------------+--------------+----------------+--------------
--+-----------------+
```

Como se puede notar había presencia de valores faltantes para las columnas Country, City, Postal_Code, Legislative_District, Vehicle_Location, Electric_Utility y 200_Census_Tract. La columna con la mayor cantidad de valores faltantes era Legislative_District con un porcentaje del 0.22%. A pesar de contar con estos valores nulos se puede tomar la decisión de eliminarlos ya que no afectarían en gran magnitud la eliminación de estos registros.

In [12]:
```python
# Contar duplicados
df.select("*").groupBy(df.columns).count().filter("count > 1").show()
```

```
+---+------+----+-----+-----------+----------+----+-----+---------------------+----+----
----------+---------+--------------------+--------------+----------------+--------------
--+-----------------+-----+
|VIN|County|City|State|Postal_Code|Model_Year|Make|Model|Electric_Vehicle_Type|CAFV|Elec
tric_Range|Base_MSRP|Legislative_District|DOL_Vehicle_ID|Vehicle_Location|Electric_Utili
ty|2020_Census_Tract|count|
+---+------+----+-----+-----------+----------+----+-----+---------------------+----+----
----------+---------+--------------------+--------------+----------------+--------------
--+-----------------+-----+
+---+------+----+-----+-----------+----------+----+-----+---------------------+----+----
----------+---------+--------------------+--------------+----------------+--------------
--+-----------------+-----+
```

No se encontró presencia de valores duplicados.

In [13]:
```python
df.describe().show()
```

```
+-------+----------+------+--------+------+-----------------+------------------+--------
------------+------------------+---------------------+---------------------+------------
----+-----------------+--------------------+-------------------+--------------------+---
-----------------+--------------------+
|summary|       VIN|County|    City| State|      Postal_Code|        Model_Year|
        Make|             Model|Electric_Vehicle_Type|                 CAFV|    Electric_R
ange|        Base_MSRP|Legislative_District|     DOL_Vehicle_ID|    Vehicle_Location|
Electric_Utility|   2020_Census_Tract|
+-------+----------+------+--------+------+-----------------+------------------+--------
------------+------------------+---------------------+---------------------+------------
----+-----------------+--------------------+-------------------+--------------------+---
-----------------+--------------------+
|  count|    200048|200044|  200044|200048|           200044|            200048|
      200048|            200048|               200048|               200048|           20
0048|           200048|              199606|             200048|              200040|
          200044|              200044|
|   mean|      null|  null|    null|  null|98176.17812081342|2020.8712608973847|
        null| 500.5304568527919|                 null|                 null|53.4852785331
5204|947.5519125409902|  28.986062543210124|2.262987746758728E8|                null|
            null|5.297544652417358...|
| stddev|      null|  null|    null|  null|2424.207811187193| 2.994933121794512|
        null|14.890633447473123|                 null|                 null|88.7863006692
9003|7860.591090711001|  14.908108304680836|7.282432541963586E7|                null|
            null|1.605628439899456 5E9|
|    min|1C4JJXN60P|   Ada|Aberdeen|    AE|             1731|              1997|
       ACURA|              330E| Battery Electric ...|Clean Alternative...|
   0|                0|                   1|               4385|POINT (-100.48613...|
      AVISTA CORP|          1001020100|
```

```
|    max|ZFAFFAC45R|  Yuba|  Zillah|    WY|            99577|                2025|WHEEGO E
LECTRIC CARS|                ZDX| Plug-in Hybrid El...|Not eligible due ...|
337|          845000|                  49|          479254772|POINT (-98.711755...|PUGE
T SOUND ENERG...|          56021001100|
+--------+----------+------+--------+------+------------------+------------------+--------
------------+-------------------+----------------------+---------------------+-------------
----+------------------+--------------------+--------------------+---------------------+---
-----------------+--------------------+
```

De acuerdo con la tabla anterior podemos ver el Rango eléctrico de los vehículos en la base de datos tiene una media de 53.48, una desviación estándar de 88.78, un mínimo de 0 y un máximo de 337. Las demás variables se toman como categóricas.

In [16]:
```
df.groupBy("Make").count().orderBy("count", ascending=False).show()
```

```
+-------------+-----+
|         Make|count|
+-------------+-----+
|        TESLA|88083|
|    CHEVROLET|14806|
|       NISSAN|14416|
|         FORD|10547|
|          KIA| 8763|
|          BMW| 8295|
|       TOYOTA| 7681|
|   VOLKSWAGEN| 5565|
|      HYUNDAI| 5476|
|         JEEP| 5288|
|       RIVIAN| 5213|
|        VOLVO| 4707|
|         AUDI| 4074|
|     CHRYSLER| 3620|
|MERCEDES-BENZ| 1879|
|      PORSCHE| 1220|
|       SUBARU| 1167|
|     POLESTAR| 1112|
|         MINI| 1011|
|   MITSUBISHI| 1007|
+-------------+-----+
only showing top 20 rows
```

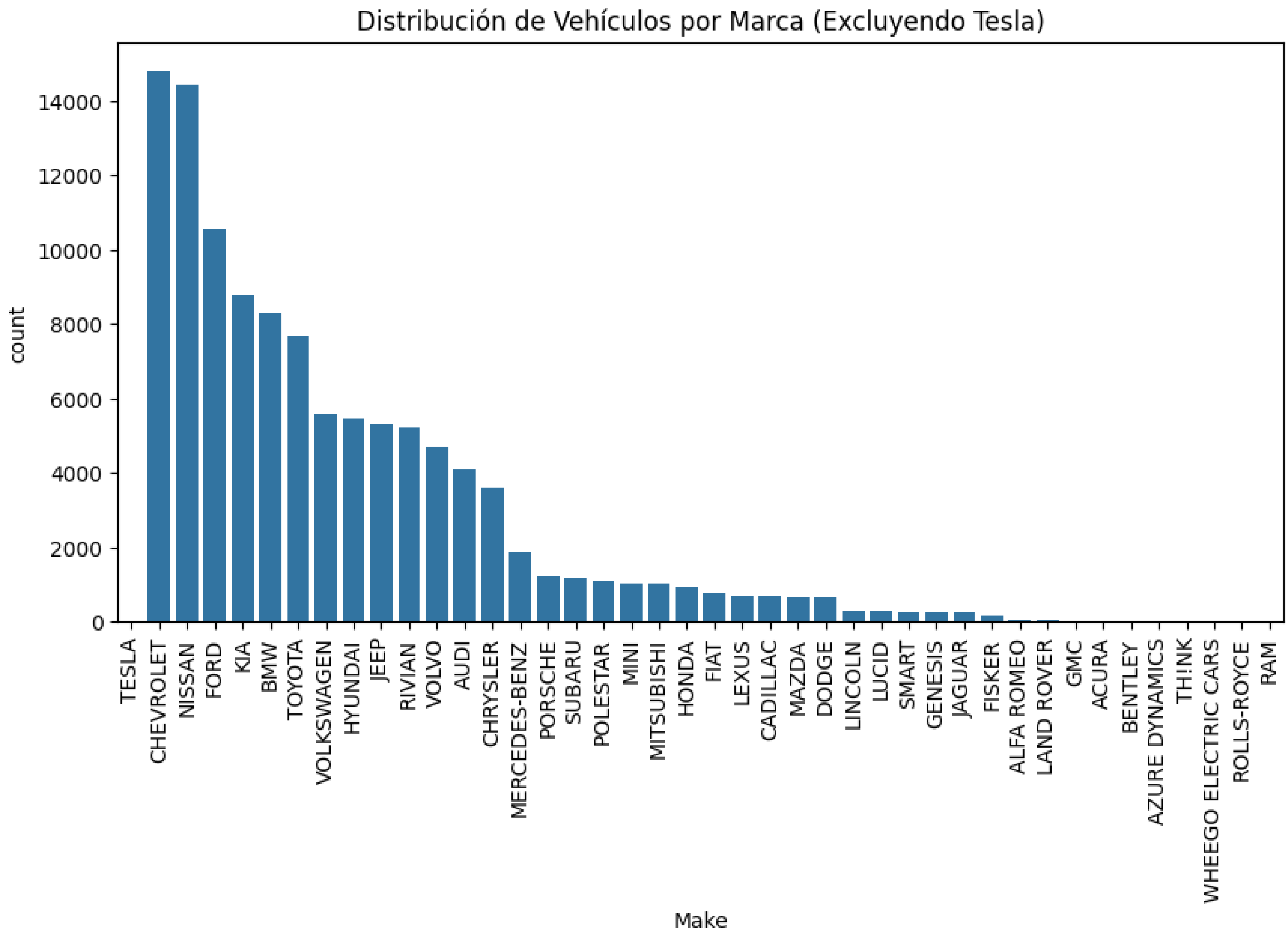
En la tabla anterior se puede detallar la cantidad de vehículos eléctricos que había en la base de datos discriminados por marca fabricante. En total TESLA es la que mayor población de vehículos eléctricos tiene con modelos desde 1997 y hasta 2025, esto corresponde al 44% de los datos. Una de las marcas fabricantes con menos vehículos es MITSUBISHI con un porcentaje del 0.5%.

In [17]:
```
df.groupBy("CAFV").count().orderBy("count", ascending=False).show()
```

```
+--------------------+------+
|                CAFV| count|
+--------------------+------+
|Eligibility unkno...|109401|
|Clean Alternative...| 69622|
|Not eligible due ...| 21025|
+--------------------+------+
```

Se puede detallar que la tabla anterior hace referencia a la elegibilidad de los vehículos para ser considerados vehículos de combustible alternativo limpio en función de su rango de batería. Aproximadamente la elegibilidad del 55% de los vehículos en la base de datos es desconocida porque no se ha investigado o verificado el rango de la batería del vehículo. Ahora, el 35% son vehículos elegibles para ser clasificados como vehículos de combustible alternativo limpio. Y, por último, el 11% de estos vehículos no son elegibles para ser clasificados como vehículos de combustible alternativo limpio porque su rango de batería es bajo.

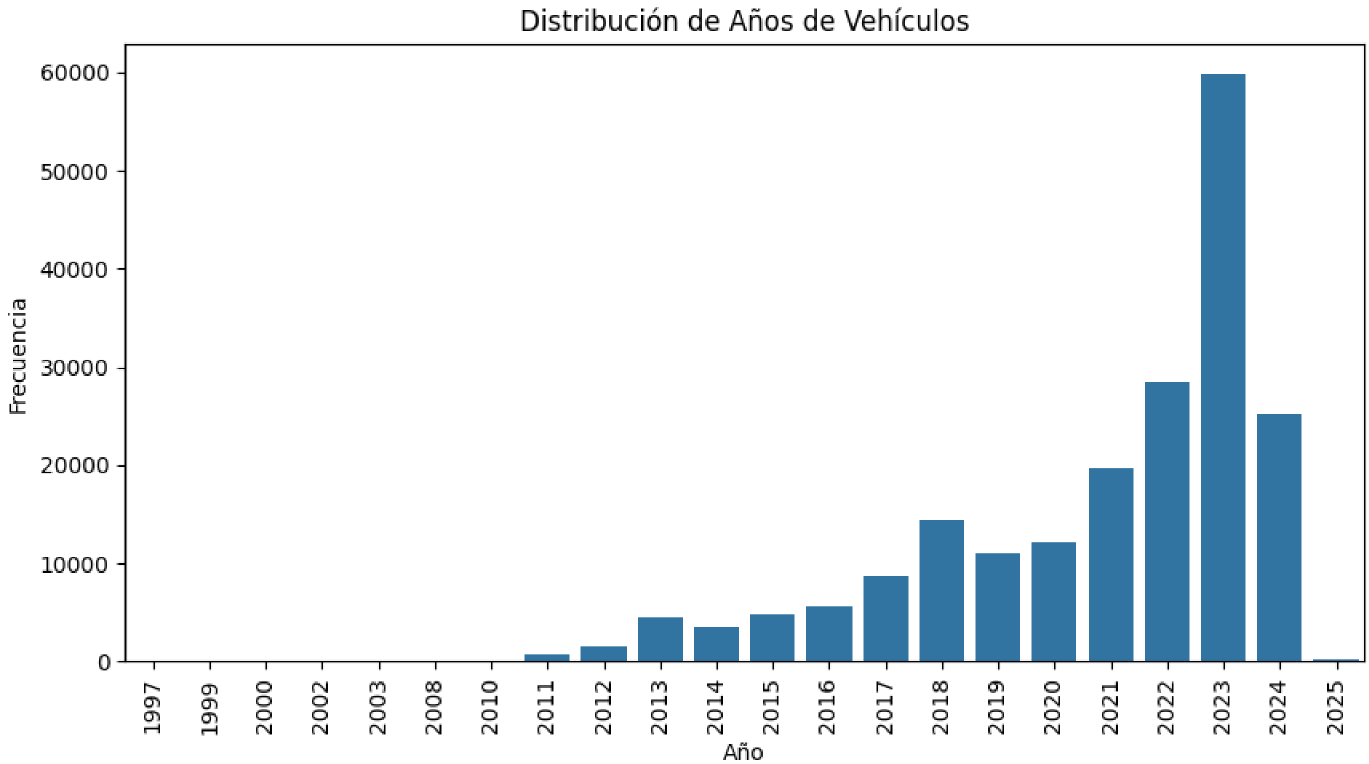
In [19]:
```
# Convertir a pandas Para graficar
pandas_df = df.toPandas()

plt.figure(figsize=(10,5))
# Filtrar el DataFrame y crear el gráfico de barras en una línea
sns.countplot(data=pandas_df[pandas_df['Make'] != 'TESLA'], x='Make', order=pandas_df['M

plt.xticks(rotation=90)
plt.title('Distribución de Vehículos por Marca (Excluyendo Tesla)')
plt.show()
```




Como se puede notar en la anterior grafica (sin contar Tesla, ya que ella ocupa el 44% de los datos), se puede ver que las marcas con una fuerte participación en el mercado de vehículos eléctricos son CHEVROLET y NISSAN con un porcentaje en conjunto del 15%. Además, se puede ver que las marcas GMC, ACURA, BENTLEY, AZURE DYNAMICS THINKS, WHHEGO ELECTRIC CARS, ROLLS-RIYCE y RAM tienen una menor participación en el mercado.

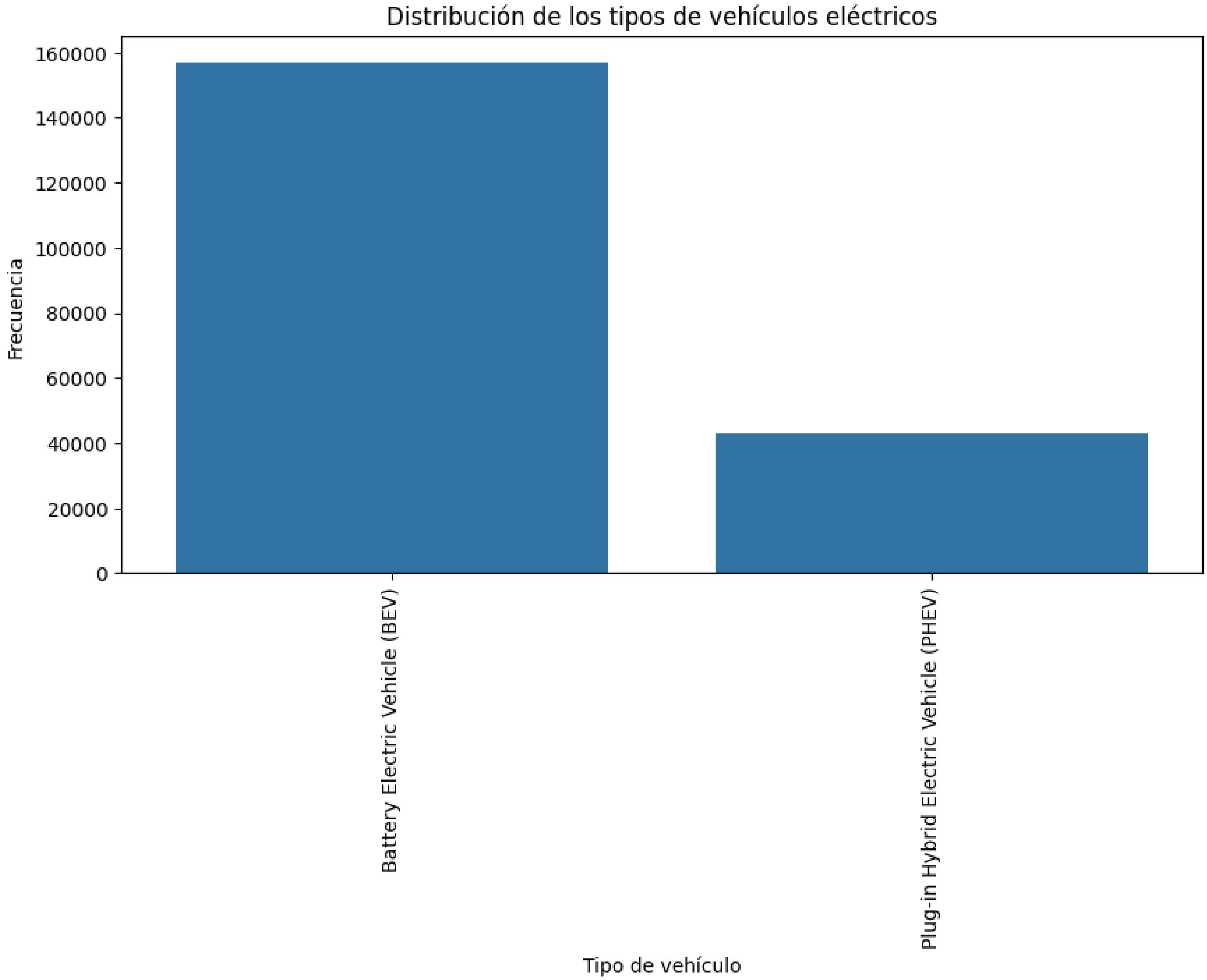
In [20]:
```
# Contar la frecuencia de cada año
year_counts = pandas_df['Model_Year'].value_counts().sort_index()
plt.figure(figsize=(10,5))

# Crear el gráfico de barras
sns.barplot(x=year_counts.index, y=year_counts.values)
```

```
plt.title('Distribución de Años de Vehículos')
plt.xlabel('Año')
plt.ylabel('Frecuencia')
plt.xticks(rotation=90)
plt.show()
```




La gráfica anterior muestra los años con mayor distribución de vehículos eléctricos. Este comportamiento es comprensible, ya que los avances tecnológicos recientes han facilitado el desarrollo de fuentes de energía más limpias y sostenibles en comparación con años anteriores. Es importante destacar que se observa un pico significativo en los vehículos modelo 2023, que representa aproximadamente el 30% del total.

In [23]:
```
# Contar la frecuencia de cada tipo de vehiculo electrico
year_counts = pandas_df['Electric_Vehicle_Type'].value_counts().sort_index()
plt.figure(figsize=(10,5))

# Crear el gráfico de barras
sns.barplot(x=year_counts.index, y=year_counts.values)

plt.title('Distribución de los tipos de vehículos eléctricos')
plt.xlabel('Tipo de vehículo')
plt.ylabel('Frecuencia')
plt.xticks(rotation=90)
plt.show()
```



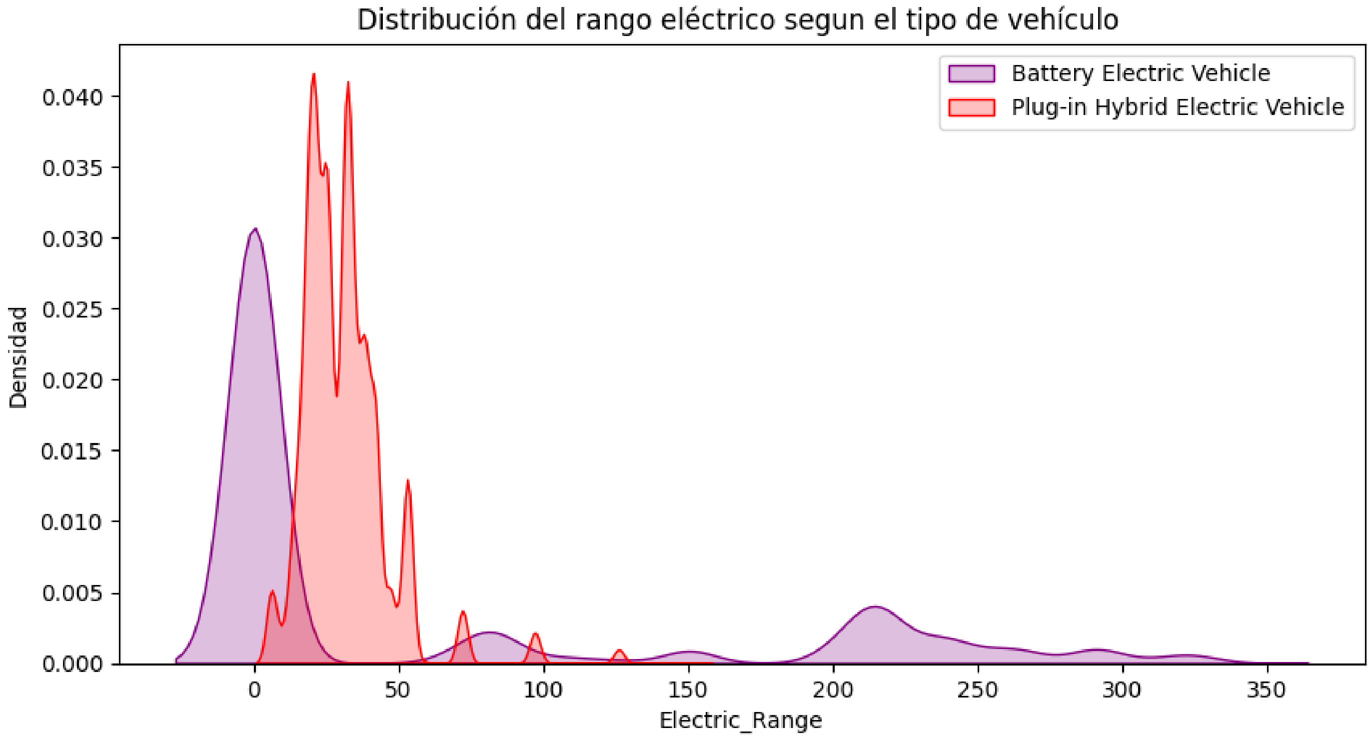

En la grafica anterior se puede notar que la mayoría de los vehículos en la base de datos son vehículos eléctricos de batería esto corresponde al 75% de los datos, el restante corresponde a vehículos eléctricos híbridos enchufables.

In [144…

```
# Configuramos el tamaño de la figura
plt.figure(figsize=(10, 5))

var_num = 'Electric_Range'
sns.kdeplot(pandas_df.loc[pandas_df['Electric_Vehicle_Type'] == "Battery Electric Vehicl
sns.kdeplot(pandas_df.loc[pandas_df['Electric_Vehicle_Type'] == "Plug-in Hybrid Electric
plt.title(f'Distribución del rango eléctrico segun el tipo de vehículo ')
plt.xlabel(var_num)
plt.ylabel('Densidad')
plt.legend()
plt.show()
```

```
<ipython-input-144-b738b6b18f30>:5: FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(pandas_df.loc[pandas_df['Electric_Vehicle_Type'] == "Battery Electric Vehi
cle (BEV)", var_num], shade=True, color='purple', label='Battery Electric Vehicle')
<ipython-input-144-b738b6b18f30>:6: FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.
```

```
  sns.kdeplot(pandas_df.loc[pandas_df['Electric_Vehicle_Type'] == "Plug-in Hybrid Electr
ic Vehicle (PHEV)", var_num], shade=True, color='red', label='Plug-in Hybrid Electric Ve
hicle')
```




El gráfico anterior muestra las distribuciones del rango eléctrico de los vehículos en la base de datos según el tipo de vehículo, ya sean vehículos eléctricos de batería o vehículos eléctricos híbridos enchufables.

In [80]:
```
# Agregar latitud y longitud

df = df.withColumn('loc_longitude', regexp_extract('Vehicle_Location', r'POINT \(([-\d.]
       .withColumn('loc_latitude', regexp_extract('Vehicle_Location', r'POINT \(([-\d.]+

# Mostrar el DataFrame original con las nuevas columnas
df.show(truncate=False)
```

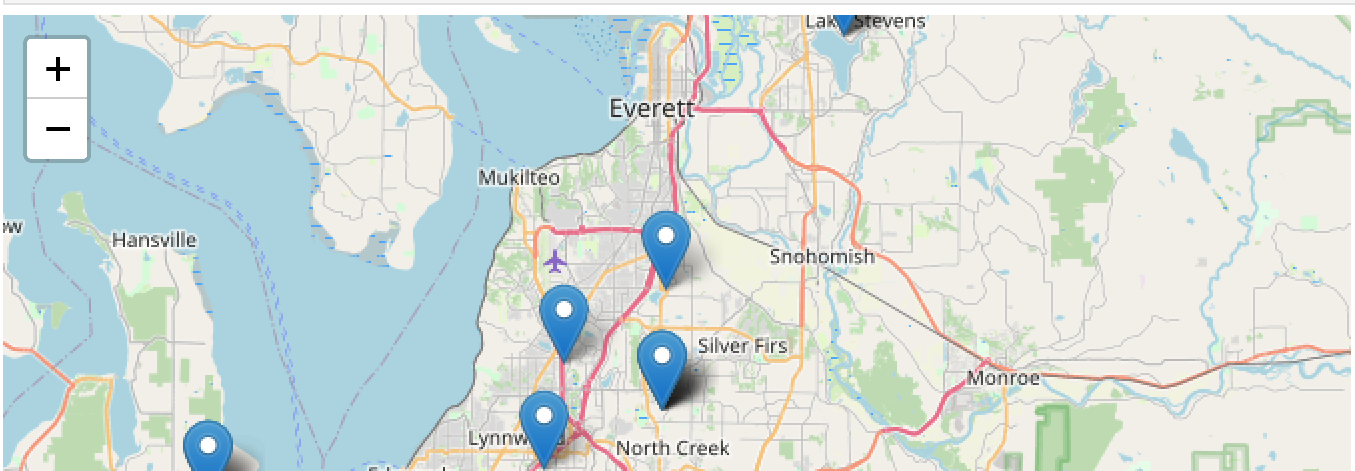
```
+----------+---------+------------+-----+-----------+----------+---------+-------+------
--------------------------------+-----------------------------------------------------
-----+--------------+---------+---------------------+--------------+---------------------
----------+--------------------------------------------+------------------+-------------+
------------+
|VIN       |County   |City        |State|Postal_Code|Model_Year|Make     |Model  |Electr
ic_Vehicle_Type                 |CAFV
     |Electric_Range|Base_MSRP|Legislative_District|DOL_Vehicle_ID|Vehicle_Location
          |Electric_Utility                            |2020_Census_Tract|loc_longitude|
loc_latitude|
+----------+---------+------------+-----+-----------+----------+---------+-------+------
--------------------------------+-----------------------------------------------------
-----+--------------+---------+---------------------+--------------+---------------------
----------+--------------------------------------------+------------------+-------------+
------------+
|5YJ3E1EB0J|Thurston |Olympia     |WA   |98512      |2018      |TESLA    |MODEL 3|Batter
y Electric Vehicle (BEV)        |Clean Alternative Fuel Vehicle Eligible
     |215           |0        |35                  |104823078     |POINT (-122.957046 4
6.991391)   |PUGET SOUND ENERGY INC                       |53067012730      |-122.957046
|46.991391   |
|WA1AAAGE9M|Kitsap   |Port Orchard|WA   |98367      |2021      |AUDI     |E-TRON |Batter
y Electric Vehicle (BEV)        |Clean Alternative Fuel Vehicle Eligible
     |222           |0        |35                  |156660507     |POINT (-122.6530052 4
7.4739066)|PUGET SOUND ENERGY INC                       |53035092901      |-122.6530052 |
47.4739066  |
|5YJ3E1EA2J|Yakima   |Yakima      |WA   |98902      |2018      |TESLA    |MODEL 3|Batter
```

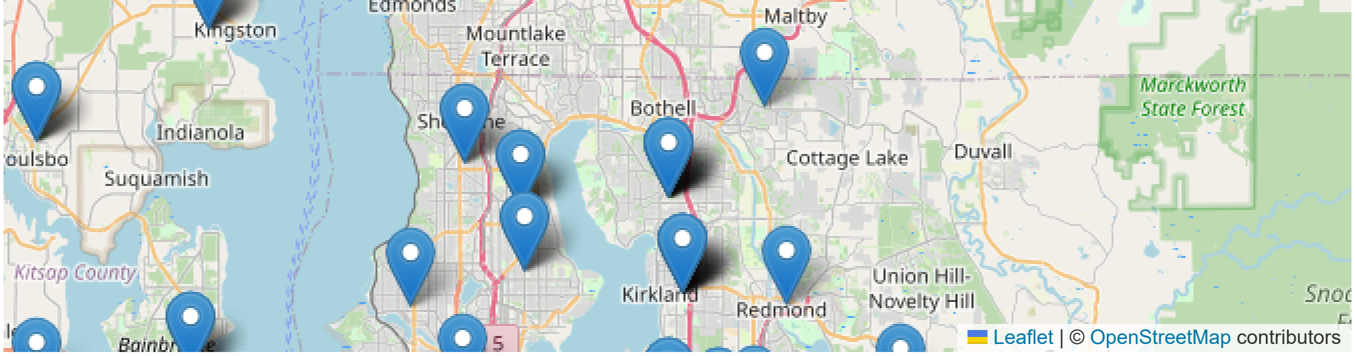
```
y Electric Vehicle (BEV)        |Clean Alternative Fuel Vehicle Eligible
     |215           |0        |14                    |269374108     |POINT (-120.530331 4
6.59534)   |PACIFICORP                                    |53077000500      |-120.530331
|46.59534    |
|5YJ3E1EA4N|Yakima   |Yakima      |WA   |98902      |2022       |TESLA    |MODEL 3|Batter
y Electric Vehicle (BEV)        |Eligibility unknown as battery range has not been resea
rched|0             |0        |15                    |213383894     |POINT (-120.530331 4
6.59534)   |PACIFICORP                                    |53077001202      |-120.530331
|46.59534    |
|7SAYGAEE2P|Snohomish|Bothell     |WA   |98012      |2023       |TESLA    |MODEL Y|Batter
y Electric Vehicle (BEV)        |Eligibility unknown as battery range has not been resea
rched|0             |0        |1                     |229496046     |POINT (-122.206146 4
7.839957)  |PUGET SOUND ENERGY INC                        |53061052009      |-122.206146
|47.839957   |
|WBY1Z4C51E|Yakima   |Yakima      |WA   |98908      |2014       |BMW      |I3     |Plug-i
n Hybrid Electric Vehicle (PHEV)|Clean Alternative Fuel Vehicle Eligible
     |72            |0        |14                    |8045817       |POINT (-120.611068 4
6.596645)  |PACIFICORP                                    |53077000401      |-120.611068
|46.596645   |
|5YJSA1DPXC|Thurston |Olympia     |WA   |98502      |2012       |TESLA    |MODEL S|Batter
y Electric Vehicle (BEV)        |Clean Alternative Fuel Vehicle Eligible
     |265           |59900    |22                    |188634442     |POINT (-122.943445 4
7.059252)  |PUGET SOUND ENERGY INC                        |53067010600      |-122.943445
|47.059252   |
|5YJSA1H27F|Yakima   |Yakima      |WA   |98908      |2015       |TESLA    |MODEL S|Batter
y Electric Vehicle (BEV)        |Clean Alternative Fuel Vehicle Eligible
     |208           |0        |14                    |109175566     |POINT (-120.611068 4
6.596645)  |PACIFICORP                                    |53077002900      |-120.611068
|46.596645   |
|7FCTGBAA7P|Kitsap   |Poulsbo     |WA   |98370      |2023       |RIVIAN   |R1T    |Batter
y Electric Vehicle (BEV)        |Eligibility unknown as battery range has not been resea
rched|0             |0        |23                    |262803131     |POINT (-122.6368884 4
7.7469547)|PUGET SOUND ENERGY INC                       |53035090400      |-122.6368884 |
47.7469547  |
|3C3CFFGE7H|King     |Seattle     |WA   |98103      |2017       |FIAT     |500    |Batter
y Electric Vehicle (BEV)        |Clean Alternative Fuel Vehicle Eligible
     |84            |0        |43                    |9411349       |POINT (-122.3499053 4
7.673887) |CITY OF SEATTLE - (WA)|CITY OF TACOMA - (WA)|53033004600      |-122.3499053 |
47.673887   |
|1FMCU0LZ4M|Kitsap   |Silverdale  |WA   |98383      |2021       |FORD     |ESCAPE |Plug-i
n Hybrid Electric Vehicle (PHEV)|Clean Alternative Fuel Vehicle Eligible
     |38            |0        |23                    |260383966     |POINT (-122.7035285 4
7.660204) |PUGET SOUND ENERGY INC                       |53035091302      |-122.7035285 |
47.660204   |
|5YJSA1H14E|Snohomish|Snohomish   |WA   |98296      |2014       |TESLA    |MODEL S|Batter
y Electric Vehicle (BEV)        |Clean Alternative Fuel Vehicle Eligible
     |208           |69900    |1                     |225773271     |POINT (-122.121841 4
7.841036)  |PUGET SOUND ENERGY INC                        |53061052112      |-122.121841
|47.841036   |
|5YJYGDEEXL|Snohomish|Everett     |WA   |98208      |2020       |TESLA    |MODEL Y|Batter
y Electric Vehicle (BEV)        |Clean Alternative Fuel Vehicle Eligible
     |291           |0        |44                    |121781950     |POINT (-122.2032349 4
7.8956271)|PUGET SOUND ENERGY INC                       |53061041610      |-122.2032349 |
47.8956271  |
|1G1RD6E42C|Yakima   |Yakima      |WA   |98901      |2012       |CHEVROLET|VOLT   |Plug-i
n Hybrid Electric Vehicle (PHEV)|Clean Alternative Fuel Vehicle Eligible
     |35            |0        |14                    |222080204     |POINT (-120.4688751 4
6.6046178)|PACIFICORP                                   |53077000100      |-120.4688751 |
46.6046178  |
|1FADP5CU9G|Thurston |Olympia     |WA   |98502      |2016       |FORD     |C-MAX  |Plug-i
n Hybrid Electric Vehicle (PHEV)|Not eligible due to low battery range
     |19            |0        |22                    |201044532     |POINT (-122.943445 4
7.059252)  |PUGET SOUND ENERGY INC                        |53067010520      |-122.943445
|47.059252   |
|1N4AZ1CP3J|Island   |Coupeville  |WA   |98239      |2018       |NISSAN   |LEAF   |Batter
y Electric Vehicle (BEV)        |Clean Alternative Fuel Vehicle Eligible
```

```
     |151            |0         |10                    |290902181     |POINT (-122.6591616 4
8.1982108)|PUGET SOUND ENERGY INC                          |53029971000      |-122.6591616 |
48.1982108  |
|5YJ3E1EB3N|Yakima   |Yakima      |WA   |98902      |2022      |TESLA    |MODEL 3|Batter
y Electric Vehicle (BEV)         |Eligibility unknown as battery range has not been resea
rched|0               |0         |15                    |207337504     |POINT (-120.530331 4
6.59534)   |PACIFICORP                                   |53077001202      |-120.530331
|46.59534    |
|WA1LAAGE2P|Thurston |Yelm        |WA   |98597      |2023      |AUDI     |E-TRON |Batter
y Electric Vehicle (BEV)         |Eligibility unknown as battery range has not been resea
rched|0               |0         |2                     |227506191     |POINT (-122.5715761 4
6.9095798)|PUGET SOUND ENERGY INC                          |53067012530      |-122.5715761 |
46.9095798  |
|1FADP3R44D|Kitsap   |Poulsbo     |WA   |98370      |2013      |FORD     |FOCUS  |Batter
y Electric Vehicle (BEV)         |Clean Alternative Fuel Vehicle Eligible
     |76             |0         |23                    |121439048     |POINT (-122.6368884 4
7.7469547)|PUGET SOUND ENERGY INC                          |53035090502      |-122.6368884 |
47.7469547  |
|5YJ3E1EB3J|Island   |Greenbank   |WA   |98253      |2018      |TESLA    |MODEL 3|Batter
y Electric Vehicle (BEV)         |Clean Alternative Fuel Vehicle Eligible
     |215            |0         |10                    |127230512     |POINT (-122.566915 4
8.089609)  |PUGET SOUND ENERGY INC                           |53029971302      |-122.566915
|48.089609   |
+----------+---------+------------+-----+----------+----------+---------+-------+------
---------------------------------+-----------------------------------------------------
-----+--------------+---------+---------------------+--------------+--------------------
----------+----------------------------------------------+-----------------+-------------+
------------+
only showing top 20 rows
```

In [151…

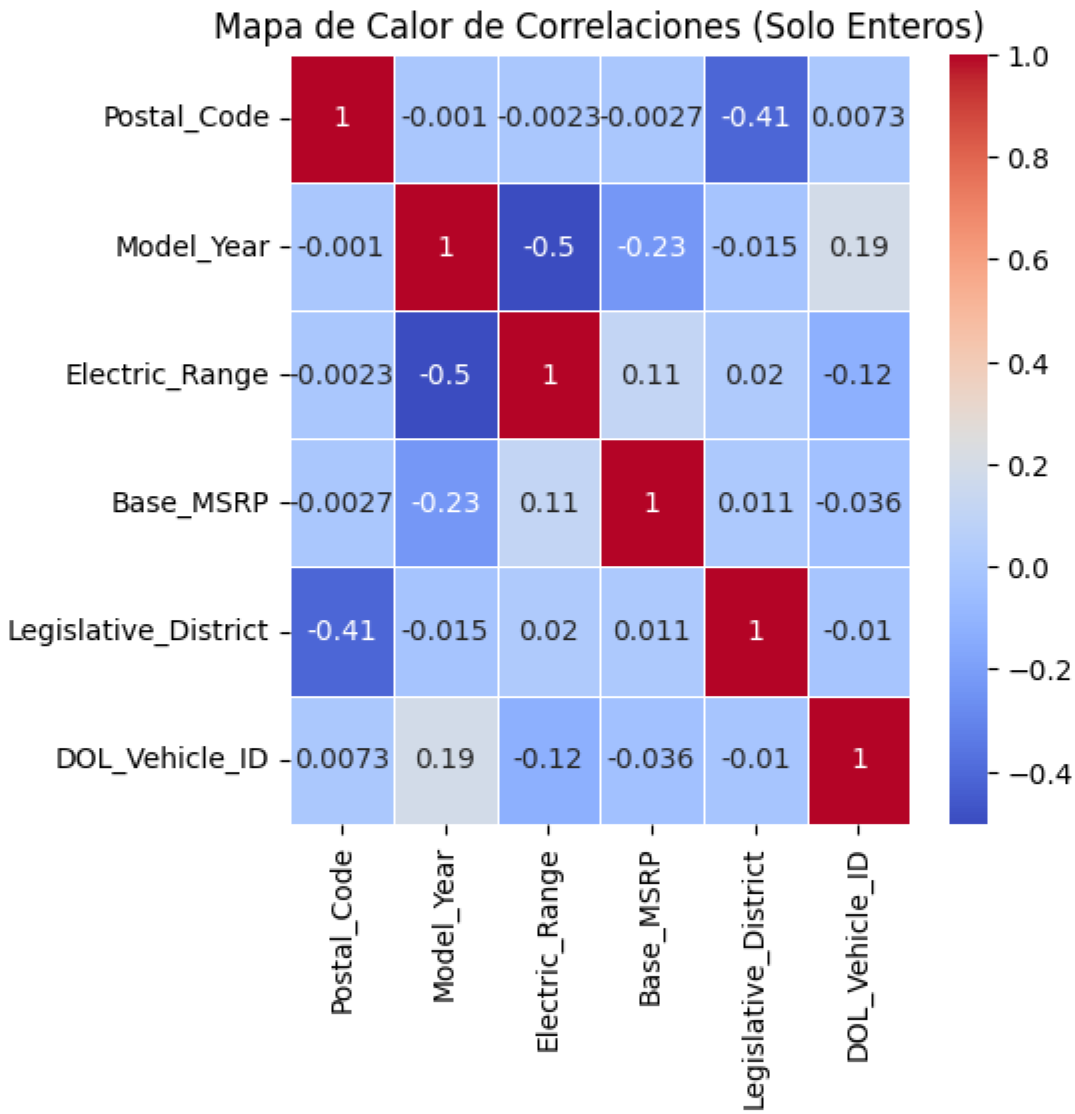
```python
df_2013 = df.filter(df["Model_Year"] == 2023)
df_filtered = df_2013.na.drop(subset=["loc_latitude", "loc_longitude"]).limit(100)

# Convertir el DataFrame de PySpark a Pandas
df_pandas = df_filtered.select("loc_latitude", "loc_longitude").toPandas()

# Crear un mapa centrado en una ubicación inicial (puedes ajustarla según tu necesidad)
mapa = folium.Map(location=[47.839957, -122.206146], zoom_start=10)

# Recorrer las filas del DataFrame y agregar marcadores
for i, row in df_pandas.iterrows():
    lat = row['loc_latitude']
    lon = row['loc_longitude']
    folium.Marker([lat, lon], popup=f'Lat: {lat}, Lon: {lon}').add_to(mapa)

# Guardar el mapa en un archivo HTML
mapa.save('mapa_marcadores.html')

# Mostrar el mapa interactivo en el notebook (si estás en un entorno que lo soporte)
display(mapa)
```






El gráfico anterior es una muestra de 100 ubicaciones de los vehículos eléctricos de modelo año 2013.

In [24]:
```
# Seleccionar solo columnas de tipo entero
integer_columns = [field.name for field in df.schema.fields if isinstance(field.dataType

# Seleccionar solo esas columnas
df_integers = df.select(integer_columns)
# Convertir a pandas
pandas_df_integers = df_integers.toPandas()


plt.figure(figsize = (5,5))

# Calcular la matriz de correlación
corr_matrix = pandas_df_integers.corr()

# Crear el mapa de calor
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', linewidths=0.5)

# Mostrar el gráfico
plt.title('Mapa de Calor de Correlaciones (Solo Enteros)')
plt.show()
```




En el anterior grafico se puede detallar las correlaciones entre las variables numéricas, una de las correlaciones altas moderadas es entre el modelo del vehículo y el rango eléctrico esta relación está influenciada por varios factores tecnológicos y de diseño que mejoran con el tiempo. A medida que los fabricantes lanzan nuevos modelos, suelen integrar avances que impactan directamente en el rendimiento de la batería y, por lo tanto, en la autonomía del vehículo.

Otra relación alta moderada se da entre el distrito legislativo y el código postal en el contexto de los vehículos eléctricos puede ser relevante en términos de políticas públicas, incentivos fiscales y regulaciones locales que afectan la adopción y distribución de estos vehículos. Cada distrito legislativo puede tener diferentes normativas o incentivos para promover el uso de vehículos eléctricos, lo que podría influir en la cantidad y tipo de vehículos registrados en ciertos códigos postales.

### Usando deequ para calidad de datos

In [25]:
```
analysisResult = AnalysisRunner(spark) \
                    .onData(df) \
                    .addAnalyzer(Size()) \
                    .addAnalyzer(Completeness("Electric_Range")) \
                    .addAnalyzer(Completeness("DOL_Vehicle_ID")) \
                    .addAnalyzer(Distinctness("Electric_Range")) \
                    .addAnalyzer(Mean("Base_MSRP")) \
                    .addAnalyzer(CountDistinct("Electric_Vehicle_Type")) \
                    .addAnalyzer(MaxLength("Electric_Vehicle_Type")) \
                    .addAnalyzer(Minimum("DOL_Vehicle_ID")) \
```

```
                    .addAnalyzer(Maximum("DOL_Vehicle_ID")) \
                    .run()

analysisResult_df = AnalyzerContext.successMetricsAsDataFrame(spark, analysisResult)
analysisResult_df.show()
```

```
+-------+--------------------+------------+--------------------+
| entity|            instance|        name|               value|
+-------+--------------------+------------+--------------------+
| Column|      Electric_Range| Distinctness|5.198752299448132E-4|
| Column|           Base_MSRP|        Mean|   947.5519125409902|
| Column|Electric_Vehicle_...|   MaxLength|                38.0|
|Dataset|                   *|        Size|            200048.0|
| Column|Electric_Vehicle_...|CountDistinct|                2.0|
| Column|      DOL_Vehicle_ID| Completeness|                1.0|
| Column|      DOL_Vehicle_ID|     Minimum|              4385.0|
| Column|      DOL_Vehicle_ID|     Maximum|         4.79254772E8|
| Column|      Electric_Range| Completeness|                1.0|
+-------+--------------------+------------+--------------------+
```

```
/usr/local/lib/python3.10/dist-packages/pyspark/sql/dataframe.py:127: UserWarning: DataF
rame constructor is internal. Do not directly use it.
  warnings.warn("DataFrame constructor is internal. Do not directly use it.")
```

Como se puede observar en los resultados anteriores, por ejemplo, para la variable Electric_Range, este valor podría indicar la proporción de registros en los que aparece un valor específico dentro de la variable, es decir, un valor aparece en aproximadamente el 0.0519% de los registros.

Para Base_MSRP nos indica que el precio de Venta Sugerido por el Fabricante promeido es de 947.55.

El tipo de vehículo eléctrico Plug-in Hybrid Electric Vehicle (PHEV) es el que mas caracteres tenia.

El total de vehículos eléctricos en la base de datos son 200048.

El total de valores distintos en tipos de vehículos es 2.

La variable DOL Vehicle ID con un valor de 1 nos indica que todos los registros o campos necesarios están presentes y tienen valores no nulos o no vacíos. Esto es importante ya que se garantiza la calidad y fiabilidad de los datos antes de utilizarlos en análisis, informes o modelos. Su valor mínimo es de 4385 y su valor máximo es de 4.79E8. COMPLETAR.

Para la variable Electric_rangue también tenemos un valor de 1 lo que nos indica que todos los registros o campos necesarios están presentes y tienen valores no nulos o no vacíos.

## Profiling

In [26]:
```
result = ColumnProfilerRunner(spark) \
             .onData(df) \
             .run()
```

In [27]:
```
for col, profile in result.profiles.items():
    print(f'Column \'{col}\'')
    print('\t',f'completeness: {profile.completeness}')
    print('\t',f'approximate number of distinct values: {profile.approximateNumDistinctV
    print('\t',f'datatype: {profile.dataType}')
```

```
Column 'CAFV'
         completeness: 1.0
         approximate number of distinct values: 3
         datatype: String
Column 'VIN'
```

```
        completeness: 1.0
        approximate number of distinct values: 12399
        datatype: String
Column 'Make'
        completeness: 1.0
        approximate number of distinct values: 38
        datatype: String
Column 'Vehicle_Location'
        completeness: 0.9999600095976966
        approximate number of distinct values: 953
        datatype: String
Column 'Postal_Code'
        completeness: 0.9999800047988483
        approximate number of distinct values: 936
        datatype: Integral
Column 'Electric_Utility'
        completeness: 0.9999800047988483
        approximate number of distinct values: 80
        datatype: String
Column 'Legislative_District'
        completeness: 0.9977905302727346
        approximate number of distinct values: 49
        datatype: Integral
Column 'Model'
        completeness: 1.0
        approximate number of distinct values: 146
        datatype: String
Column 'Electric_Range'
        completeness: 1.0
        approximate number of distinct values: 108
        datatype: Integral
Column 'County'
        completeness: 0.9999800047988483
        approximate number of distinct values: 192
        datatype: String
Column 'City'
        completeness: 0.9999800047988483
        approximate number of distinct values: 787
        datatype: String
Column 'Base_MSRP'
        completeness: 1.0
        approximate number of distinct values: 32
        datatype: Integral
Column 'DOL_Vehicle_ID'
        completeness: 1.0
        approximate number of distinct values: 212051
        datatype: Integral
Column 'Model_Year'
        completeness: 1.0
        approximate number of distinct values: 21
        datatype: Integral
Column 'Electric_Vehicle_Type'
        completeness: 1.0
        approximate number of distinct values: 2
        datatype: String
Column 'State'
        completeness: 1.0
        approximate number of distinct values: 47
        datatype: String
Column '2020_Census_Tract'
        completeness: 0.9999800047988483
        approximate number of distinct values: 2140
        datatype: Integral
```

En el resultado anterior se puede detallar las variables en las cuales sus registros o campos necesarios están presentes y tienen valores no nulos o no vacíos, son aquellas con valor 1, para las otras quiere decir que hay presencia de valores faltantes y son columnas que tienen su calidad comprometida. También se puede destacaran la cantidad de valores distintos en cada una de ellas, además del tipo de dato.

In [28]:
```
totalNumber_profile = result.profiles['Electric_Range']

print(f'Statistics of \'Electric_Range\':')
print('\t',f"minimum: {totalNumber_profile.minimum}")
print('\t',f"maximum: {totalNumber_profile.maximum}")
print('\t',f"mean: {totalNumber_profile.mean}")
print('\t',f"standard deviation: {totalNumber_profile.stdDev}")
```

```
Statistics of 'Electric_Range':
	 minimum: 0.0
	 maximum: 337.0
	 mean: 53.48527853315204
	 standard deviation: 88.78607875652003
```

In [29]:
```
totalNumber_profile = result.profiles['DOL_Vehicle_ID']

print(f'Statistics of \'DOL_Vehicle_ID\':')
print('\t',f"minimum: {totalNumber_profile.minimum}")
print('\t',f"maximum: {totalNumber_profile.maximum}")
print('\t',f"mean: {totalNumber_profile.mean}")
print('\t',f"standard deviation: {totalNumber_profile.stdDev}")
```

```
Statistics of 'DOL_Vehicle_ID':
	 minimum: 4385.0
	 maximum: 479254772.0
	 mean: 226298774.6758728
	 standard deviation: 72824143.40227896
```

En el anterior resultado se puede destacar el máximo, mínimo, el promedio y la desviación estándar tanto para la variable Electric_range como la variable DOL_Vehicle_ID. Para el caso de la primera tenemos un mínimo de 0 y un máximo de 337, además de un promedio de rango eléctrico de 53.48. Para la segunda tenemos como promedio 226298774 y una desviación estándar de 72824143.

In [30]:
```
status_profile = result.profiles['Electric_Vehicle_Type']

print('Value distribution in \'Electric_Vehicle_Type\':')
for unique_entry in status_profile.histogram:
    print('\t',f"{unique_entry.value} occurred {unique_entry.count} times (ratio is {uni
```

```
Value distribution in 'Electric_Vehicle_Type':
	 Battery Electric Vehicle (BEV) occurred 156956 times (ratio is 0.78459169799248
19)
	 Plug-in Hybrid Electric Vehicle (PHEV) occurred 43092 times (ratio is 0.2154083
020075182)
```

In [31]:
```
status_profile = result.profiles['CAFV']

print('Value distribution in \'CAFV\':')
for unique_entry in status_profile.histogram:
    print('\t',f"{unique_entry.value} occurred {unique_entry.count} times (ratio is {uni
```

```
Value distribution in 'CAFV':
	 Clean Alternative Fuel Vehicle Eligible occurred 69622 times (ratio is 0.348026
4736463249)
	 Not eligible due to low battery range occurred 21025 times (ratio is 0.10509977
60537471)
	 Eligibility unknown as battery range has not been researched occurred 109401 ti
mes (ratio is 0.546873750299928)
```

En los anteriores resultados se muestran la cantidad de valores únicos en las variables Electric_Vehicle_Type y CAFV, además de su proporción de aparición en la base de datos. Por ejemplo, para la primera variable, el valor con un porcentaje de ocurrencia del 78% es Battery Electric Vehicle (BEV). Y para la segunda variable, el valor Eligibility unknown as battery range has not been researched es la de mayor ocurrencia con un porcentaje del 55% aproximadamente.

### Anomaly Detection

In [81]:
```
df_2013 = df.filter(df["Model_Year"] == 2013)
df_2013.show(5)
```

```
+----------+--------+-------+-----+-----------+----------+---------+-----+--------------
-------+--------------------+--------------+---------+--------------------+-------------
-+--------------------+--------------------+-----------------+-------------+------------
+
|       VIN|  County|   City|State|Postal_Code|Model_Year|     Make|Model|Electric_Vehic
le_Type|                CAFV|Electric_Range|Base_MSRP|Legislative_District|DOL_Vehicle_I
D|    Vehicle_Location|    Electric_Utility|2020_Census_Tract|loc_longitude|loc_latitude
|
+----------+--------+-------+-----+-----------+----------+---------+-----+--------------
-------+--------------------+--------------+---------+--------------------+-------------
-+--------------------+--------------------+-----------------+-------------+------------
+
|1FADP3R44D|  Kitsap|Poulsbo|   WA|      98370|      2013|     FORD|FOCUS| Battery Elect
ric ...|Clean Alternative...|            76|        0|                  23|     12143904
8|POINT (-122.63688...|PUGET SOUND ENERG...|      53035090502| -122.6368884|  47.7469547
|
|1N4AZ0CP2D|    King|Seattle|   WA|      98144|      2013|   NISSAN| LEAF| Battery Elect
ric ...|Clean Alternative...|            75|        0|                  37|     23615393
5|POINT (-122.30165...|CITY OF SEATTLE -...|      53033010002| -122.3016563|  47.5858977
|
|1N4AZ0CP7D|  Yakima| Wapato|   WA|      98951|      2013|   NISSAN| LEAF| Battery Elect
ric ...|Clean Alternative...|            75|        0|                  15|     21115011
0|POINT (-120.44861...|          PACIFICORP|      53077940007|  -120.448617|  46.4426932
|
|1N4AZ0CPXD|  Yakima| Yakima|   WA|      98902|      2013|   NISSAN| LEAF| Battery Elect
ric ...|Clean Alternative...|            75|        0|                  14|     19525015
6|POINT (-120.53033...|          PACIFICORP|      53077000800|  -120.530331|    46.59534
|
|1G1RH6E47D|Thurston|Olympia|   WA|      98516|      2013|CHEVROLET| VOLT| Plug-in Hybri
d El...|Clean Alternative...|            38|        0|                  22|     26334072
4|POINT (-122.78083...|PUGET SOUND ENERG...|      53067012221|   -122.78083|   47.083975
|
+----------+--------+-------+-----+-----------+----------+---------+-----+--------------
-------+--------------------+--------------+---------+--------------------+-------------
-+--------------------+--------------------+-----------------+-------------+------------
+
only showing top 5 rows
```

In [82]:
```
df_2023 = df.filter(df["Model_Year"] == 2023)
df_2023.show(5)
```

```
+----------+---------+---------+-----+-----------+----------+------+-------+------------
---------+--------------------+--------------+---------+--------------------+----------
---+--------------------+--------------------+-----------------+-------------+----------
--+
|       VIN|   County|     City|State|Postal_Code|Model_Year|  Make|  Model|Electric_Veh
icle_Type|                CAFV|Electric_Range|Base_MSRP|Legislative_District|DOL_Vehicle
_ID|    Vehicle_Location|    Electric_Utility|2020_Census_Tract|loc_longitude|loc_latitu
de|
+----------+---------+---------+-----+-----------+----------+------+-------+------------
---------+--------------------+--------------+---------+--------------------+----------
---+--------------------+--------------------+-----------------+-------------+----------
```

```
--+
|7SAYGAEE2P|Snohomish|  Bothell|   WA|      98012|      2023| TESLA|MODEL Y| Battery Ele
ctric ...|Eligibility unkno...|             0|        0|                        1|     229496
046|POINT (-122.20614...|PUGET SOUND ENERG...|      53061052009|  -122.206146|   47.8399
57|
|7FCTGBAA7P|   Kitsap|  Poulsbo|   WA|      98370|      2023|RIVIAN|    R1T| Battery Ele
ctric ...|Eligibility unkno...|             0|        0|                       23|     262803
131|POINT (-122.63688...|PUGET SOUND ENERG...|      53035090400| -122.6368884|  47.74695
47|
|WA1LAAGE2P| Thurston|     Yelm|   WA|      98597|      2023|  AUDI| E-TRON| Battery Ele
ctric ...|Eligibility unkno...|             0|        0|                        2|     227506
191|POINT (-122.57157...|PUGET SOUND ENERG...|      53067012530| -122.5715761|  46.90957
98|
|7SAYGAEE5P|   Kitsap| Kingston|   WA|      98346|      2023| TESLA|MODEL Y| Battery Ele
ctric ...|Eligibility unkno...|             0|        0|                       23|     257904
923|POINT (-122.51783...|PUGET SOUND ENERG...|      53035090102| -122.5178351|  47.79814
36|
|7SAYGDEE6P|   Kitsap|Bremerton|   WA|      98311|      2023| TESLA|MODEL Y| Battery Ele
ctric ...|Eligibility unkno...|             0|        0|                       23|     238369
785|POINT (-122.63624...|PUGET SOUND ENERG...|      53035091701|  -122.636245|    47.628
06|
+----------+---------+---------+-----+-----------+----------+------+-------+------------
---------+--------------------+--------------+---------+--------------------+-----------
---+--------------------+--------------------+-----------------+------------+----------
--+
only showing top 5 rows
```

In [83]:
```python
print(type(df_2013))
print(type(df_2023))
```

```
<class 'pyspark.sql.dataframe.DataFrame'>
<class 'pyspark.sql.dataframe.DataFrame'>
```

In [125…
```python
metricsRepository = InMemoryMetricsRepository(spark)
```

In [126…
```python
yesterdaysKey = ResultKey(spark, ResultKey.current_milli_time() - 24 * 60 * 60 * 1000)
todaysKey = ResultKey(spark, ResultKey.current_milli_time())
```

**Detección de anomalias para la media de Base_MSRP**

In [127…
```python
prev_Result = VerificationSuite(spark).onData(df_2013) \
    .useRepository(metricsRepository) \
    .saveOrAppendResult(yesterdaysKey) \
    .addAnomalyCheck(RelativeRateOfChangeStrategy(maxRateIncrease=2.0), Mean("Base_MSRP"
    .run()
```

In [128…
```python
currResult = VerificationSuite(spark).onData(df_2023) \
    .useRepository(metricsRepository) \
    .saveOrAppendResult(todaysKey) \
    .addAnomalyCheck(RelativeRateOfChangeStrategy(maxRateIncrease=2.0), Mean("Base_MSRP"
    .run()
```

In [129…
```python
print(yesterdaysKey)
print(todaysKey)
```

```
<pydeequ.repository.ResultKey object at 0x7fa1470d7ee0>
<pydeequ.repository.ResultKey object at 0x7fa1470d41c0>
```

In [130…
```python
if (currResult.status != "Success"):
    print("Anomaly detected in the Mean() metric!")
    metricsRepository.load().forAnalyzers([Mean("Base_MSRP")]).getSuccessMetricsAsDataFr
else:
    print("Non Anomlay detected in the Mean metric")
```

```
Non Anomlay detected in the Mean metric
```

### Detección de anomalias para el tamaño (Size)

In [131…
```
metricsRepository = InMemoryMetricsRepository(spark)
```

In [132…
```
prev_Result1 = VerificationSuite(spark).onData(df_2013) \
    .useRepository(metricsRepository) \
    .saveOrAppendResult(yesterdaysKey) \
    .addAnomalyCheck(RelativeRateOfChangeStrategy(maxRateIncrease=2.0), Size()) \
    .run()
```

In [133…
```
currResult1 = VerificationSuite(spark).onData(df_2023) \
    .useRepository(metricsRepository) \
    .saveOrAppendResult(todaysKey) \
    .addAnomalyCheck(RelativeRateOfChangeStrategy(maxRateIncrease=2.0), Size()) \
    .run()
```

In [134…
```
if (currResult1.status != "Success"):
    print("Anomaly detected in the Size() metric!")
    metricsRepository.load().forAnalyzers([Size()]).getSuccessMetricsAsDataFrame().show(
else:
    print("Non Anomlay detected in Size metric")
```

```
Anomaly detected in the Size() metric!
+-------+--------+----+-------+-------------+
| entity|instance|name|  value| dataset_date|
+-------+--------+----+-------+-------------+
|Dataset|       *|Size|59886.0|1726433098732|
|Dataset|       *|Size| 4384.0|1726346698713|
+-------+--------+----+-------+-------------+
```

### Detección de anomalias para la media de Electric_Range

In [135…
```
metricsRepository = InMemoryMetricsRepository(spark)
```

In [136…
```
prev_Result = VerificationSuite(spark).onData(df_2013) \
    .useRepository(metricsRepository) \
    .saveOrAppendResult(yesterdaysKey) \
    .addAnomalyCheck(RelativeRateOfChangeStrategy(maxRateIncrease=2.0), Mean("Electric_R
    .run()
```

In [137…
```
currResult = VerificationSuite(spark).onData(df_2023) \
    .useRepository(metricsRepository) \
    .saveOrAppendResult(todaysKey) \
    .addAnomalyCheck(RelativeRateOfChangeStrategy(maxRateIncrease=2.0), Mean("Electric_R
    .run()
```

In [138…
```
if (currResult.status != "Success"):
    print("Anomaly detected in the Mean metric!")
    metricsRepository.load().forAnalyzers([Mean("Electric_Range")]).getSuccessMetricsAsD
else:
    print("Non Anomlay detected in the mean metric")
```

```
Non Anomlay detected in the mean metric
```

Se pudo evidenciar normalidad en los vehículos modelo 2013 y 2023 ya que, no fueron encontradas anomalias en la media de las columnas Electric_Range y Base_MSRP. Por otro lado, si se encontro anomalia en la métrica de tamaño (Size) en estos mismos modelos (Model_Year).

In [ ]: