In [1]: ▶

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
!pip install bioinfokit
import plotly.express as px

```
Defaulting to user installation because normal site-packages is not write able
```

Requirement already satisfied: bioinfokit in c:\users\hp\appdata\roaming \python\python39\site-packages (2.1.0)

Requirement already satisfied: tabulate in c:\programdata\anaconda3\lib\s ite-packages (from bioinfokit) (0.8.9)

Requirement already satisfied: matplotlib-venn in c:\users\hp\appdata\roa ming\python\python39\site-packages (from bioinfokit) (0.11.9)

Requirement already satisfied: scikit-learn in c:\programdata\anaconda3\l ib\site-packages (from bioinfokit) (1.0.2)

Requirement already satisfied: statsmodels in c:\programdata\anaconda3\lib\site-packages (from bioinfokit) (0.13.2)

Requirement already satisfied: matplotlib in c:\programdata\anaconda3\lib \site-packages (from bioinfokit) (3.5.1)

Requirement already satisfied: pandas in c:\programdata\anaconda3\lib\sit e-packages (from bioinfokit) (1.4.2)

Requirement already satisfied: textwrap3 in c:\users\hp\appdata\roaming\python\python39\site-packages (from bioinfokit) (0.9.2)

Requirement already satisfied: numpy in c:\programdata\anaconda3\lib\site -packages (from bioinfokit) (1.21.5)

Requirement already satisfied: adjustText in c:\users\hp\appdata\roaming \python\python39\site-packages (from bioinfokit) (0.8)

Requirement already satisfied: scipy in c:\programdata\anaconda3\lib\site -packages (from bioinfokit) (1.7.3)

Requirement already satisfied: seaborn in c:\programdata\anaconda3\lib\si te-packages (from bioinfokit) (0.11.2)

Requirement already satisfied: cycler>=0.10 in c:\programdata\anaconda3\l ib\site-packages (from matplotlib->bioinfokit) (0.11.0)

Requirement already satisfied: fonttools>=4.22.0 in c:\programdata\anacon da3\lib\site-packages (from matplotlib->bioinfokit) (4.25.0)

Requirement already satisfied: packaging>=20.0 in c:\programdata\anaconda 3\lib\site-packages (from matplotlib->bioinfokit) (21.3)

Requirement already satisfied: pyparsing>=2.2.1 in c:\programdata\anacond a3\lib\site-packages (from matplotlib->bioinfokit) (3.0.4)

Requirement already satisfied: python-dateutil>=2.7 in c:\programdata\ana conda3\lib\site-packages (from matplotlib->bioinfokit) (2.8.2)

Requirement already satisfied: pillow>=6.2.0 in c:\programdata\anaconda3 \lib\site-packages (from matplotlib->bioinfokit) (9.0.1)

Requirement already satisfied: kiwisolver>=1.0.1 in c:\programdata\anacon da3\lib\site-packages (from matplotlib->bioinfokit) (1.3.2)

Requirement already satisfied: six>=1.5 in c:\programdata\anaconda3\lib\s ite-packages (from python-dateutil>=2.7->matplotlib->bioinfokit) (1.16.0) Requirement already satisfied: pytz>=2020.1 in c:\programdata\anaconda3\l

ib\site-packages (from pandas->bioinfokit) (2021.3)

Requirement already satisfied: threadpoolctl>=2.0.0 in c:\programdata\ana conda3\lib\site-packages (from scikit-learn->bioinfokit) (2.2.0)

Requirement already satisfied: joblib>=0.11 in c:\users\hp\appdata\roamin g\python\python39\site-packages (from scikit-learn->bioinfokit) (1.2.0) Requirement already satisfied: patsy>=0.5.2 in c:\programdata\anaconda3\l

ib\site-packages (from statsmodels->bioinfokit) (0.5.2)

In [2]: ▶

df = pd.read\_csv("C:\\Users\\HP\\Downloads\\Electric\_Vehicle\_Population\_Data.csv")
df.head()

## Out[2]:

	VIN (1-10)	County	City	State	ZIP Code	Model Year	Make	Model	Electric Vehicle Type	Al
										E
0	WA1AAAGE2M	Kitsap	POULSBO	WA	98370	2021	AUDI	E-TRON	Battery Electric Vehicle (BEV)	A
1	WBY8P2C00L	King	SEATTLE	WA	98122	2020	BMW	13	Battery Electric Vehicle (BEV)	Α
2	5YJXCBE21K	Cowlitz	SILVERLAKE	WA	98645	2019	TESLA	MODEL X	Battery Electric Vehicle (BEV)	Α
3	1FTZR081XY	King	SEATTLE	WA	98117	2000	FORD	RANGER	Battery Electric Vehicle (BEV)	Α
4	WBY1Z6C55H	King	SEATTLE	WA	98119	2017	BMW	13	Battery Electric Vehicle (BEV)	Α
4										<b>•</b>
Tn	[3]:									
df	.shape									

## Out[3]:

(79767, 15)

M In [4]: df.isna().sum() Out[4]: VIN (1-10) 0 5 County 0 City 0 State ZIP Code 0 Model Year 0 0 Make Model 0 Electric Vehicle Type 0 Clean Alternative Fuel Vehicle (CAFV) Eligibility 0 Electric Range Base MSRP 0 Legislative District 146 DOL Vehicle ID 0 Vehicle Location 4 dtype: int64 In [5]: M

```
df['Legislative District'].unique()
```

#### Out[5]:

```
array([23., 37., 20., 36., 45., 47., 11., 48., 2., 18., 32., 41., 42., 46., 33., 34., 6., 24., 35., 31., 28., 38., 1., 7., 5., 19., 12., 40., 27., 25., 21., 3., 49., 22., 17., 44., 10., 39., 13., 43., 8., 14., 26., 4., 16., 30., 29., 15., 9., nan])
```

In [6]: ▶

```
df['County'].unique()
```

```
Out[6]:
```

```
array(['Kitsap', 'King', 'Cowlitz', 'Thurston', 'Clark', 'Whatcom',
        'Spokane', 'Clallam', 'Pierce', 'Snohomish', 'Grays Harbor',
        'Chelan', 'San Juan', 'Mason', 'Island', 'Skagit', 'Lincoln', 'Benton', 'Yakima', 'Grant', 'Lewis', 'Jefferson', 'Kittitas',
        'Okanogan', 'Wahkiakum', 'Franklin', 'Adams', 'Walla Walla', 'Douglas', 'Skamania', 'Klickitat', 'Bell', 'Whitman', 'Arlingto
n',
        'Frederick', 'Stevens', 'Asotin', 'Nassau', 'Pacific', 'San Dieg
ο',
        'Pend Oreille', 'Montgomery', 'Sonoma', 'Liberty', 'Garfield',
        'Rockingham', 'Otero', 'District Of Columbia', 'Santa Barbara',
        'Los Angeles', 'Camden', 'Multnomah', 'Bradley', 'Muscogee',
        'Columbia', 'Placer', 'Anne Arundel', 'Alexandria City',
        'Monterey', 'Chaves', 'Ferry', nan, 'Chesapeake City', 'Fairfax',
        'Norfolk City', 'New Castle', 'Wilson', 'Charles', 'Honolulu',
        'Saint Clair', 'Alameda', 'Bexar', 'Lake', 'Fresno', 'Riverside',
        'Suffolk City', 'Contra Costa', 'Santa Clara', 'El Paso',
        'New London', 'Glacier', 'Orange', 'Harrison', 'Okaloosa', 'Brya
n',
        'Tulare', 'Prince William', 'Dekalb', 'Dorchester', 'Saint Marys',
        'Saginaw', 'Newport', 'Klamath', 'Shelby', 'Ventura',
        'Leavenworth', 'Howard', 'Riley', 'Sacramento', 'Oldham', 'Stafford', 'Goochland', 'Meade', 'San Francisco', 'Bartow',
        'Maricopa', 'Moore', 'Kent', 'Cumberland', 'Ozaukee', 'Passaic',
        'Middlesex', 'Saint Louis', 'Caddo'], dtype=object)
```

In [7]: ▶

```
df['Vehicle Location'].unique()
```

```
Out[7]:
```

```
array(['POINT (-122.63339300000001 47.748427)',
       'POINT (-122.303413 47.61065)', 'POINT (-122.772699 46.32052
6)',
       'POINT (-122.379354 47.687571)',
       'POINT (-122.36772100000002 47.639264)',
       'POINT (-122.0427239999999 47.623594)',
       'POINT (-122.266685 47.308313)', 'POINT (-122.204248 47.71927
8)',
       'POINT (-122.276826 47.449726)', 'POINT (-122.188994 47.67840
6)',
       'POINT (-122.558621 46.888349)',
       'POINT (-122.40849800000001 45.620943)',
       'POINT (-122.37015900000002 47.743354)',
       'POINT (-122.168422 47.614824)', 'POINT (-122.151342 47.56019
2)',
       'POINT (-122.33024199999998 48.904379)',
       'POINT (-122.297534 47.685291)', 'POINT (-122.028168 47.58617
```

In [8]: M df['Legislative District'].max() Out[8]: 49.0 H In [9]: df.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 79767 entries, 0 to 79766 Data columns (total 15 columns): Non-Null Count D # Column type ----------0 79767 non-null o VIN (1-10) bject 79762 non-null o County 1 bject 2 City 79767 non-null o bject 3 State 79767 non-null o bject 4 ZIP Code 79767 non-null i nt64 Model Year 79767 non-null i 5 nt64 79767 non-null o 6 Make bject 79767 non-null o Model 7 bject 79767 non-null o Electric Vehicle Type bject Clean Alternative Fuel Vehicle (CAFV) Eligibility 79767 non-null o 9 bject 10 Electric Range 79767 non-null i nt64 11 Base MSRP 79767 non-null i nt64 12 Legislative District 79621 non-null f loat64 13 DOL Vehicle ID 79767 non-null i nt64

memory usage: 9.1+ MB

Vehicle Location

dtypes: float64(1), int64(5), object(9)

14 'bject

79763 non-null o

In [10]:

```
df.columns
```

## Out[10]:

In [11]: ▶

```
df.dtypes
```

#### Out[11]:

VIN (1-10) County City State ZIP Code Model Year Make Model Electric Vehicle Type Clean Alternative Fuel Vehicle (CAFV) Eligibility Electric Range Base MSRP Legislative District DOL Vehicle ID Vehicle Location	object object object int64 int64 object object object int64 int64 float64 int64 object
dtype: object	

In [12]:

df.isnull()

## Out[12]:

	VIN (1- 10)	County	City	State	ZIP Code	Model Year	Make	Model	Electric Vehicle Type	Clean Alternative Fuel Vehicle (CAFV) Eligibility	Electri Rang
0	False	False	False	False	False	False	False	False	False	False	Fals
1	False	False	False	False	False	False	False	False	False	False	Fals
2	False	False	False	False	False	False	False	False	False	False	Fals
3	False	False	False	False	False	False	False	False	False	False	Fals
4	False	False	False	False	False	False	False	False	False	False	Fals
79762	False	False	False	False	False	False	False	False	False	False	Fals
79763	False	False	False	False	False	False	False	False	False	False	Fals
79764	False	False	False	False	False	False	False	False	False	False	Fals
79765	False	False	False	False	False	False	False	False	False	False	Fals
79766	False	False	False	False	False	False	False	False	False	False	Fals

79767 rows × 15 columns

In [13]:

df.isnull().sum()

## Out[13]:

VIN (1-10)	0
County	5
City	0
State	0
ZIP Code	0
Model Year	0
Make	0
Model	0
Electric Vehicle Type	0
Clean Alternative Fuel Vehicle (CAFV) Eligibility	0
Electric Range	0
Base MSRP	0
Legislative District	146
DOL Vehicle ID	0
Vehicle Location	4
dtype: int64	

M

In [14]: ▶

df.dropna

Out[14]:

```
<bound method DataFrame.dropna of</pre>
                                           VIN (1-10)
                                                         County
                                                                        City
       ZIP Code Model Year
0
       WA1AAAGE2M
                                                   98370
                     Kitsap
                                POULSB0
                                            WA
                                                                 2021
1
                                                    98122
       WBY8P2C00L
                       King
                                SEATTLE
                                            WA
                                                                 2020
2
                    Cowlitz
       5YJXCBE21K
                             SILVERLAKE
                                            WA
                                                   98645
                                                                 2019
3
       1FTZR081XY
                       King
                                SEATTLE
                                            WA
                                                   98117
                                                                 2000
4
       WBY1Z6C55H
                       King
                                SEATTLE
                                            WA
                                                    98119
                                                                 2017
79762
       JA4J24A5XJ
                       King
                                SEATTLE
                                                    98115
                                                                 2018
                                            WΑ
                                                                 2020
79763
       1G1FZ6S07L
                    Spokane
                              DEER PARK
                                            WΑ
                                                   99006
79764515YJYGDEE4L
                       King
                                SEATTLE
                                            WΑ
                                                   98112
                                                                 2020
                                                                                          M
79765 1G1FZ6S06L
                     Pierce
                               LAKEWOOD
                                            WA
                                                   98498
                                                                 2020
₫97€6df5₡₫9₫₫₫₫$9Ј
                    Spokane
                                SPOKANE
                                            WΑ
                                                    99223
                                                                 2018
             Make
                        Model
                                         Electric Vehicle Type
ān [16]:
                                                                                          M
             AUDI
                       E-TRON
                               Battery Electric Vehicle (BEV)
              BMW
                               Battery Electric Vehicle (BEV)
                           13
āf.isnull().
            FEB [Y
                      MODEL X
                               Battery Electric Vehicle (BEV)
3
             FORD
                       RANGER
                               Battery Electric Vehicle (BEV)
               BMW
                               Battery Electric Vehicle (BEV)
Out[16]:
                    OUTLANDER
                               Battery Electric Vehicle (BEV)
79M621-MOTSUBISHI
                               Battery Electric Vehicl@ (BEV)
₹8₩8₹
        CHEVROLET
                      BOLT EV
                               Battery Electric Vehicl@ (BEV)
79764
            TESLA
                      MODEL Y
                               Battery Electric Vehicl@ (BEV)
        CHEVROLET
                      BOLT EV
39365
Z9766ode
            TESLA
                      MODEL 3
                               Battery Electric Vehicl@ (BEV)
Model Year
Make Clean Alternative Fuel Vehicle (CAFV) Eligibility
                                                           Electric Range
Model
@lectric VehicleClepe Alternative Fuel Vehicle Eligib@e
                                                                        222
Clean AlternativeleanlAVehroativeAFvelEVebibleitvigibbe
                                                                        153
Electric Range Clean Alternative Fuel Vehicle Eligib@e
                                                                        289
Base MSRP
                Clean Alternative Fuel Vehicle Eligib@e
                                                                         58
                                                                         81
4egislative Dist6lean Alternative Fuel Vehicle Eligib@e
DOL Vehicle ID
                                                                        . . .
V@N62le Location Not eligible due to low battery range
                                                                        22
                Clean Alternative Fuel Vehicle Eligible
                                                                        259
₹₹1 int64
                 Clean Alternative Fuel Vehicle Eligible
                                                                        291
79764
79765
                 Clean Alternative Fuel Vehicle Eligible
                                                                        259
                                                                        215
FXPLORA
       Base MSRP
                   Legislative District DOL Vehicle ID
0
               0
                                    23.0
                                               148815901
1
               0
                                    37.0
                                               132197810
2
               0
                                    20.0
                                               154341673
3
               0
                                    36.0
                                               169378338
4
               0
                                    36.0
                                               192605101
. . .
                                     . . .
                                                      . . .
               0
                                               476074686
79762
                                    46.0
79763
               0
                                     7.0
                                               127165531
79764
               0
                                    43.0
                                               127108670
               0
79765
                                    28.0
                                               141902162
79766
                                     6.0
                                               328614947
                             Vehicle Location
0
       POINT (-122.63339300000001 47.748427)
1
                 POINT (-122.303413 47.61065)
2
               POINT (-122.772699 46.320526)
3
               POINT (-122.379354 47.687571)
4
       POINT (-122.36772100000002 47.639264)
```

```
79762 POINT (-122.297534 47.685291)

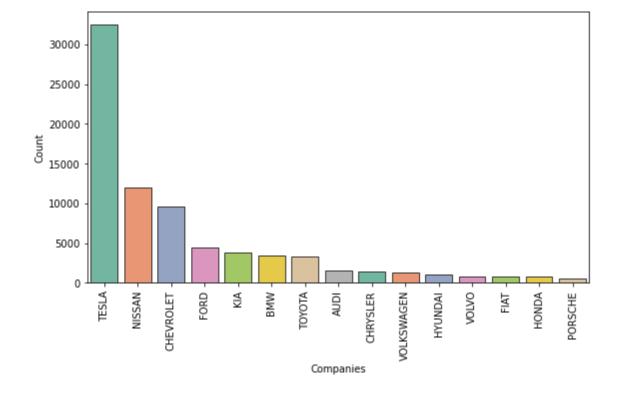
†97637]: POINT (-117.481417 47.949511)

79764
County 56466 47.631708)
County 56450471(2344)
Values = df.groupby('County', 56450471(2)
Values
```

In [18]: ▶

```
Companies = df.groupby('Make').count().sort_values(by='City',ascending=False)['City'].ir
values = df.groupby('Make').count().sort_values(by='City',ascending=False)['City'].value

plt.figure(figsize=(9,5))
sns.barplot(x=list(Companies)[:15],y=values[:15],edgecolor='.2',palette='Set2')
plt.xticks(rotation='90')
plt.xlabel('Companies')
plt.ylabel('Count')
plt.show()
```

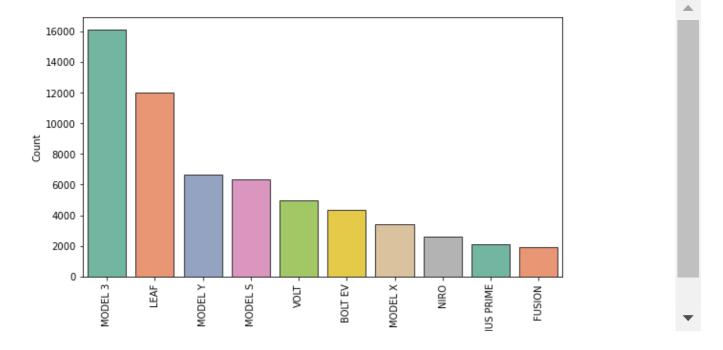


In [19]: ▶

px.pie(names=list(Companies)[:15], values=values[:15], width=500, height=600)

In [20]: ▶

```
Models = df.groupby('Model').count().sort_values(by='City',ascending=False)['City'].indevalues = df.groupby('Model').count().sort_values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City'].values(by='City',ascending=False)['City',ascending=False)['City',ascending=False)['City',ascending=False)['City',ascending=False)['City',ascending=
```



In [21]: ▶

```
#Percentage of BEV vs PHEV

Vehicle_type = list(df.groupby('Electric Vehicle Type').count()['County'].index)
values = df.groupby('Electric Vehicle Type').count()['County'].values

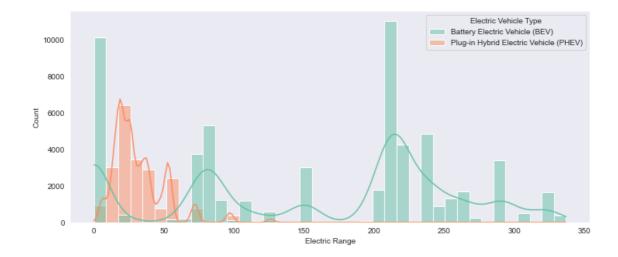
px.pie(names=Vehicle_type,values=values,height=400)
```

In [22]:

```
#lets see the electric range difference between PHEV and BEV
plt.figure(figsize=(12,5))
sns.set_style(style='dark')
sns.histplot(x = 'Electric Range',data=df,kde=True,hue='Electric Vehicle Type',palette='
```

## Out[22]:

<AxesSubplot:xlabel='Electric Range', ylabel='Count'>



In [23]: ▶

```
data_bev = df[df['Electric Vehicle Type']!='Plug-in Hybrid Electric Vehicle (PHEV)']
companies=list(data_bev.groupby('Make').count().sort_values(by='City',ascending=False)['data_bev['bev'] = data_bev['Make'].apply(lambda x:1 if x in companies else 0 )
data_bev = data_bev[data_bev['bev']==1]

plt.figure(figsize=(10,5))
sns.kdeplot(x='Electric Range',hue='Make',data=data_bev)
```

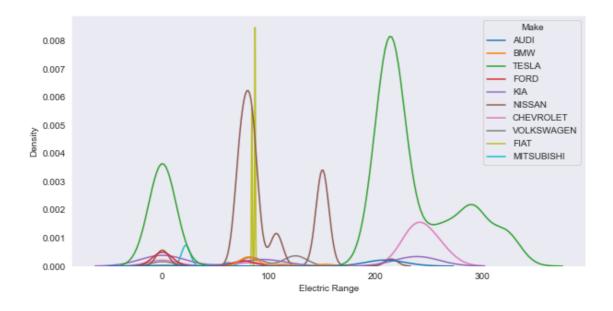
C:\Users\HP\AppData\Local\Temp\ipykernel\_1532\535499912.py:3: SettingWith
CopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame. Try using .loc[row\_indexer,col\_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy)

#### Out[23]:

<AxesSubplot:xlabel='Electric Range', ylabel='Density'>



In [24]: ▶

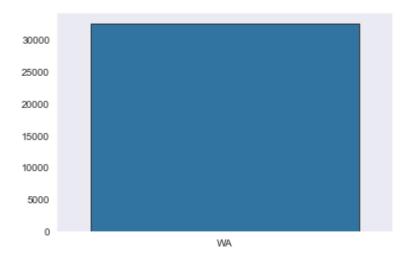
```
data_TESLA = df[df['Make']=='TESLA']
top_10_states_TESLA = list(data_TESLA.groupby('State').count().sort_values(by='City',asc
values = list(data_TESLA.groupby('State').count().sort_values(by='City',ascending=False)
```

In [25]: ▶

```
sns.barplot(x = top_10_states_TESLA,y=values,edgecolor='.2')
```

### Out[25]:

#### <AxesSubplot:>

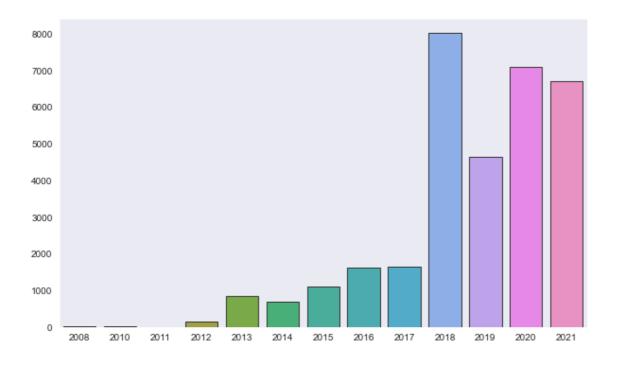


In [26]: ▶

plt.figure(figsize=(10,6))
top\_10\_year\_TESLA = list(data\_TESLA.groupby('Model Year').count().sort\_values(by='City',
values = list(data\_TESLA.groupby('Model Year').count().sort\_values(by='City',ascending=F
sns.barplot(x = top\_10\_year\_TESLA,y=values,edgecolor='.2')

## Out[26]:

#### <AxesSubplot:>

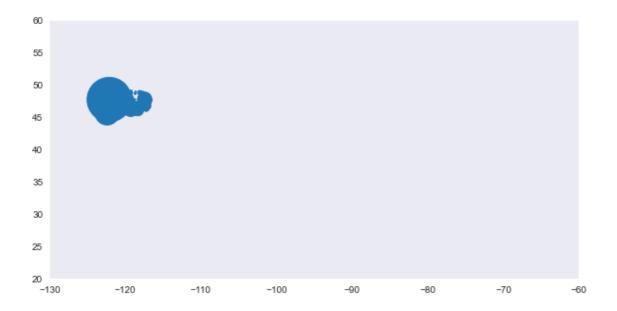


In [27]: ▶

```
locations = list(df.groupby('Vehicle Location').count()['County'].index)
values = list(df.groupby('Vehicle Location').count()['County'].values)
Location_data = pd.DataFrame({'Locations':locations,'Count':values})
Location_data['Lattitude'] = Location_data['Locations'].apply(lambda x:float(x.split(' 'Location_data['Longitude'] = Location_data['Locations'].apply(lambda x:float(x.split(' 'Phic. of the continuation of the
```

#### Out[27]:

(20.0, 60.0)



In [28]: ▶

cor\_matrix=df.corr()

In [29]:

```
sns.heatmap(cor_matrix,annot=True)
plt.show()
```



In [30]: ▶

```
df['Vehicle Location'].value_counts()
df['County'].value_counts()
df['State'].value_counts()
```

## Out[30]:

WA 79619

Name: State, dtype: int64

In [31]:

df.describe()

## Out[31]:

	ZIP Code	Model Year	Electric Range	Base MSRP	Legislative District	DOL Vehicle
count	79619.000000	79619.000000	79619.000000	79619.000000	79619.000000	7.961900e+0
mean	98258.343586	2017.630126	124.569412	2941.137794	30.156144	2.000480e+0
std	299.454690	2.575760	102.883121	13191.904432	14.581814	1.186409e+0
min	98001.000000	1993.000000	0.000000	0.000000	1.000000	4.385000e+0
25%	98052.000000	2016.000000	25.000000	0.000000	20.000000	1.284651e+0
50%	98121.000000	2018.000000	84.000000	0.000000	34.000000	1.611223e+0
75%	98370.000000	2020.000000	215.000000	0.000000	43.000000	2.556195e+0
max	99403.000000	2022.000000	337.000000	845000.000000	49.000000	4.792548e+0
4						<b>•</b>

In [32]: ▶

```
df.describe(include="all")
```

#### Out[32]:

	VIN (1-10)	County	City	State	ZIP Code	Model Year	Make	Model
count	79619	79619	79619	79619	79619.000000	79619.000000	79619	79619
unique	5196	39	425	1	NaN	NaN	32	93
top	5YJ3E1EB6J	King	SEATTLE	WA	NaN	NaN	TESLA	MODEL 3
freq	339	41740	15179	79619	NaN	NaN	32537	16139
mean	NaN	NaN	NaN	NaN	98258.343586	2017.630126	NaN	NaN
std	NaN	NaN	NaN	NaN	299.454690	2.575760	NaN	NaN
min	NaN	NaN	NaN	NaN	98001.000000	1993.000000	NaN	NaN
25%	NaN	NaN	NaN	NaN	98052.000000	2016.000000	NaN	NaN
50%	NaN	NaN	NaN	NaN	98121.000000	2018.000000	NaN	NaN
75%	NaN	NaN	NaN	NaN	98370.000000	2020.000000	NaN	NaN
max	NaN	NaN	NaN	NaN	99403.000000	2022.000000	NaN	NaN
4								•

In [33]: ▶

df.fillna(df.mode(),inplace=True)
df

C:\Users\HP\AppData\Local\Temp\ipykernel\_1532\593388003.py:1: SettingW
ithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html #returning-a-view-versus-a-copy)

#### Out[33]:

VIN (1-10) County City State ZIP Model Year Make Model Vehicle

In [34]: ▶

```
df['VIN (1-10)'].value_counts()
```

## Out[34]:

```
5YJ3E1EB6J
              339
5YJ3E1EBXJ
              336
5YJ3E1EB0J
              332
5YJ3E1EB1J
              330
5YJ3E1EB5J
              327
5YJXCBE43K
                1
WBY8P8C5XK
                1
YV4BR0PM6J
                1
KMHC75LD5J
                1
KL8CK6S09E
Name: VIN (1-10), Length: 5196, dtype: int64
```

In [35]: ▶

```
df['County'].value_counts()
```

## Out[35]:

King	41740
Snohomish	8463
Pierce	6038
Clark	4562
Thurston	3095
Kitsap	2871
Whatcom	2174
Spokane	1880
Island	980
Benton	970
Skagit	935
Clallam	579
San Juan	578
Jefferson	531
Chelan	458
Yakima	417
Cowlitz	406
Mason	391
Grays Harbor	340
Lewis	324
Kittitas	249
Franklin	239
Grant	227
Walla Walla	195
Douglas	154
Klickitat	129
Whitman	121
Pacific	111
0kanogan	108
Stevens	99
Skamania	92
Asotin	40
Adams	30
Wahkiakum	23
Lincoln	23
Pend Oreille	23
Ferry	12
Columbia	9
Garfield	3

Name: County, dtype: int64

```
H
In [36]:
df['City'].value_counts()
Out[36]:
SEATTLE
                  15179
BELLEVUE
                   4115
REDMOND
                   3127
                   2835
VANCOUVER
KIRKLAND
                   2537
BRIDGEPORT
                      1
LEWIS MCCHORD
                      1
KITTITAS
                      1
KLICKITAT
                      1
LATAH
Name: City, Length: 425, dtype: int64
In [37]:
                                                                                          M
df['State'].value_counts()
Out[37]:
      79619
WΑ
Name: State, dtype: int64
                                                                                          M
In [38]:
df['ZIP Code'].value_counts()
Out[38]:
98052
         2185
98033
         1473
98115
         1416
98004
         1366
98006
         1289
98647
            1
99116
            1
             1
98819
98227
            1
99018
Name: ZIP Code, Length: 526, dtype: int64
```

In [39]: ▶

```
df['Model Year'].value_counts()
```

## Out[39]:

```
2018
        13910
2021
        11104
2020
        11014
2019
        10595
         9853
2017
2016
         6441
         5149
2015
         4944
2013
2014
         3800
2012
         1787
2011
          871
2022
           80
           29
2010
2008
           27
            7
2000
1999
            3
            2
2002
            1
1997
            1
1998
1993
            1
```

Name: Model Year, dtype: int64

In [40]:

```
df['Make'].value_counts()
```

#### Out[40]:

**TESLA** 32537 NISSAN 12037 **CHEVROLET** 9569 4470 **FORD** 3834 KIA BMW 3464 **TOYOTA** 3327 AUDI 1622 1381 **CHRYSLER VOLKSWAGEN** 1293 HYUNDAI 1087 V0LV0 820 FIAT 779 753 **HONDA PORSCHE** 518 MITSUBISHI 514 325 MERCEDES-BENZ 293 **JEEP** 284 **SMART** 269 **JAGUAR** 192 **CADILLAC** 91 **SUBARU** 44 39 LAND ROVER 30 LINCOLN 16 **POLESTAR** 14 **FISKER** 9 AZURE DYNAMICS 3 TH!NK 2 **BENTLEY** WHEEGO ELECTRIC CARS 2 **DODGE** 

In [41]: ▶

```
df['Model'].value_counts()
```

#### Out[41]:

MODEL 3 16139 LEAF 12037 MODEL Y 6627 MODEL S 6328 VOLT 4977 918 SPYDER 1 S-10 PICKUP 1 XC90 AWD PHEV 1 **CARAVAN** 1 PRIUS PLUG-IN HYBRID Name: Model, Length: 93, dtype: int64

Name: Make, dtype: int64

```
In [42]:
                                                                                         M
df['Electric Vehicle Type'].value_counts()
Out[42]:
Battery Electric Vehicle (BEV)
                                           58383
Plug-in Hybrid Electric Vehicle (PHEV)
                                           21236
Name: Electric Vehicle Type, dtype: int64
In [43]:
                                                                                         M
df['Vehicle Location'].value_counts()
Out[43]:
POINT (-122.122018 47.678465)
                                          2185
POINT (-122.188994 47.678406)
                                          1473
POINT (-122.297534 47.685291)
                                          1416
POINT (-122.20316899999999 47.619011)
                                          1366
POINT (-122.151342 47.560192)
                                          1289
POINT (-123.45692199999999 46.303845)
                                             1
POINT (-119.0944339999999 48.280155)
                                             1
POINT (-122.478122 48.754899)
                                             1
POINT (-118.33470700000001 47.424407)
                                             1
POINT (-117.17122200000001 47.28842)
                                             1
Name: Vehicle Location, Length: 524, dtype: int64
                                                                                         M
In [44]:
df['DOL Vehicle ID'].value_counts()
Out[44]:
148815901
             1
107129088
             1
263776334
             1
247585222
             1
141108565
             1
2565741
             1
101569513
             1
243016693
             1
341041018
             1
328614947
             1
Name: DOL Vehicle ID, Length: 79619, dtype: int64
```

In [45]: ▶

```
df['Legislative District'].value_counts()
```

```
Out[45]:
41.0
        5290
45.0
        5152
48.0
        4663
36.0
        3892
46.0
        3572
43.0
        3557
1.0
        3191
5.0
        3136
34.0
        2625
37.0
        2620
22.0
        2130
40.0
        2029
23.0
        2010
18.0
        1971
32.0
        1937
21.0
        1789
44.0
        1767
11.0
        1594
26.0
        1581
10.0
        1532
24.0
        1302
17.0
        1298
47.0
        1251
42.0
        1233
31.0
        1232
27.0
        1204
49.0
        1169
35.0
        1132
33.0
        1036
39.0
        1030
28.0
        1021
2.0
         871
30.0
         863
8.0
         834
         831
38.0
25.0
         775
12.0
         704
         694
20.0
         684
6.0
         571
29.0
         536
19.0
         536
4.0
14.0
         506
         489
13.0
9.0
         422
         419
3.0
16.0
         389
7.0
         369
15.0
         180
Name: Legislative District, dtype: int64
```

localhost:8888/notebooks/Untitled12.ipynb

In [46]: ▶

```
df['Base MSRP'].value_counts()
```

## Out[46]:

ouc[40].	
0	75154
69900	1533
34600	528
31950	460
28500	232
52900	203
32250	176
38500	165
59900	153
54950	132
39995	118
44100	98
36900	87
64950	83
33950	68
45600	54
36800	52
55700	47
52650	45
34995	44
110950	29
98950	27
81100	17
53400	16
90700	16
102000	14
75095	14
35390	11
43700	11
184400	10
89100	9
109000	5
91250	3
32995	2
845000	1
66300	1
32000	1

Name: Base MSRP, dtype: int64

```
M
In [47]:
df['Electric Range'].value_counts()
Out[47]:
0
       10140
        6509
215
84
        4220
220
        4068
238
        3630
95
           2
57
           1
59
           1
80
           1
```

Name: Electric Range, Length: 99, dtype: int64

# **Lable Encoading**

```
In [48]: ▶
```

C:\Users\HP\AppData\Local\Temp\ipykernel\_1532\852114733.py:3: SettingWith
CopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame. Try using .loc[row\_indexer,col\_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy)

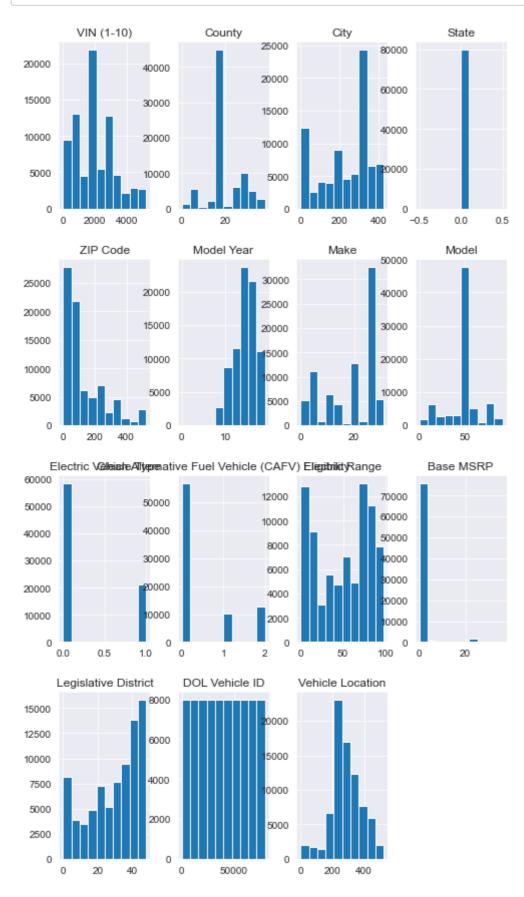
## Out[48]:

	VIN (1- 10)	County	City	State	ZIP Code	Model Year	Make	Model	Electric Vehicle Type	Clean Alternative Fuel Vehicle (CAFV) Eligibility	Electric Range
0	3857	17	291	0	202	18	0	25	0	0	80
1	4432	16	331	0	73	17	3	39	0	0	69
2	2365	7	343	0	340	16	26	51	0	0	92
3	170	16	331	0	69	4	10	68	0	0	39
4	4319	16	331	0	71	14	3	39	0	0	49
79762	2734	16	331	0	67	15	20	58	0	2	16
79763	331	31	99	0	423	17	5	14	0	0	88
79764	2620	16	331	0	66	17	26	52	0	0	93
79765	328	26	188	0	246	17	5	14	0	0	88
79766	1730	31	357	0	495	15	26	49	0	0	77

79619 rows × 15 columns

In [49]: ▶

```
plt.rcParams['figure.figsize'] = (8,15)
df.hist()
plt.show()
```



```
In [50]:
                                                                                        H
x = df.loc[:,cat].values
Х
Out[50]:
array([[ 3857,
                17,
                        291, ...,
                                       0,
                                             80, 32412],
       [ 4432,
                                             69, 21673],
                  16,
                        331, ...,
                                       0,
       [ 2365,
                                             92, 36963],
                  7,
                        343, ...,
                                       0,
                        331, ...,
                                             93, 19021],
       [ 2620,
                  16,
                                       0,
       [ 328,
                  26,
                        188, ...,
                                       0,
                                             88, 27596],
       [ 1730,
                  31,
                                             77, 67709]], dtype=int64)
                        357, ...,
                                       0,
In [51]:
                                                                                        M
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
x = sc.fit_transform(x)
In [52]:
                                                                                        M
from sklearn.decomposition import PCA
pca_model = PCA(n_components=15)
x_PCA = pca_model.fit_transform(x)
                                                                                        M
In [53]:
pca_model.explained_variance_ratio_
Out[53]:
array([1.78444593e-01, 1.13900292e-01, 9.97819324e-02, 9.01390547e-02,
       8.82027945e-02, 7.43801855e-02, 7.04183261e-02, 6.85851572e-02,
       5.69727295e-02, 4.76542824e-02, 4.41496947e-02, 3.31887554e-02,
       2.44178576e-02, 9.76434472e-03, 1.17700961e-33])
In [54]:
                                                                                        H
X = df.iloc[:,[3,4]].values
```

## K-means clustering

```
In [55]:

from sklearn.cluster import KMeans
```

```
In [56]:

wcss = []
for i in range(1,11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', random_state = 42)
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)
```

```
In [57]:

wcss
```

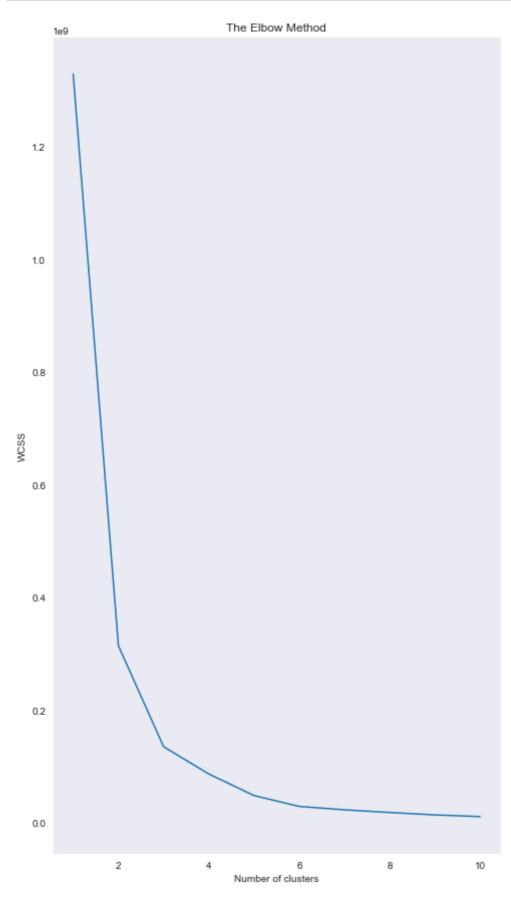
#### Out[57]:

```
[1328957249.9840012, 314294678.4677549, 135019505.17092726, 86574080.20231578, 48266749.99067938, 28996394.16967954, 22933193.055935137, 18223294.409017555, 13888757.80920052, 10900144.928630024]
```

## **Elbow Curve**

In [58]: ▶

```
plt.plot(range(1,11), wcss)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```

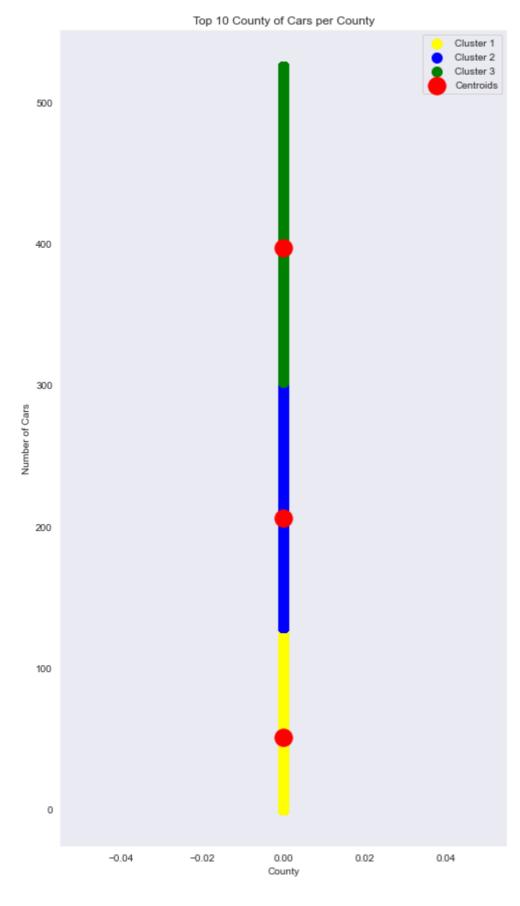


```
In [59]:
kmeans = KMeans(n_clusters = 3,init = 'k-means++', random_state = 42)

In [60]:

y_kmeans = kmeans.fit_predict(X)
```

In [68]: ▶





## **DBSCAN CLUSTERING**

```
M
In [62]:
from sklearn.cluster import DBSCAN
In [63]:
                                                                                        M
dbs = DBSCAN(eps=5, min_samples=5)
In [64]:
                                                                                        M
y_dbs = dbs.fit_predict(X)
In [65]:
y_dbs
Out[65]:
array([0, 0, 0, ..., 0, 0, 0], dtype=int64)
                                                                                        H
In [66]:
np.unique(y_dbs)
Out[66]:
array([0], dtype=int64)
```

In [67]:

```
plt.scatter(X[y_dbs == -1, 0], X[y_dbs == -1, 1],s = 100, c = 'yellow', label = 'Cluster
plt.scatter(X[y_dbs == 0, 0], X[y_dbs == 0, 1],s = 100, c = 'blue', label = 'Cluster 0')
plt.scatter(X[y_dbs == 1, 0], X[y_dbs == 1, 1], s = 100, c = 'green', label = 'Cluster 1'
plt.scatter(X[y_dbs == 2, 0], X[y_dbs == 2, 1],s = 100, c = 'pink', label = 'Cluster 2')
plt.scatter(X[y_dbs == 3, 0], X[y_dbs == 3, 1],s = 100, c = 'red', label = 'Cluster 3')
plt.title('Top 10 County of Cars per County')
plt.xlabel('County')
plt.ylabel('Number of Cars')
plt.legend()
plt.show()
```

