In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [5]:
```
data = pd.read_csv('D:\Shravan\Laptop Data\Innomatics\DataScience-GenAI Internship 2024\Electric_Vehicles_EDA\dataset.csv')
data.head()
```

Out[5]:

	VIN (1-10)	County	City	State	Postal Code	Model Year	Make	Model	Electric Vehicle Type	Clean Alternative Fuel Vehicle (CAFV) Eligibility	Electric Range	Base MSRP	Legislative District	DOL Vehicle ID	Vehicl Locatio
0	JTMEB3FV6N	Monroe	Key West	FL	33040	2022	TOYOTA	RAV4 PRIME	Plug-in Hybrid Electric Vehicle (PHEV)	Clean Alternative Fuel Vehicle Eligible	42	0	NaN	198968248	POIN (-81.8002 24.554!
1	1G1RD6E45D	Clark	Laughlin	NV	89029	2013	CHEVROLET	VOLT	Plug-in Hybrid Electric Vehicle (PHEV)	Clean Alternative Fuel Vehicle Eligible	38	0	NaN	5204412	POIN (-114.5724 35.1681!
2	JN1AZ0CP8B	Yakima	Yakima	WA	98901	2011	NISSAN	LEAF	Battery Electric Vehicle (BEV)	Clean Alternative Fuel Vehicle Eligible	73	0	15.0	218972519	POIN (-120.5072 46.6044
3	1G1FW6S08H	Skagit	Concrete	WA	98237	2017	CHEVROLET	BOLT EV	Battery Electric Vehicle (BEV)	Clean Alternative Fuel Vehicle Eligible	238	0	39.0	186750406	POIN (-121.751 48.5389
4	3FA6P0SU1K	Snohomish	Everett	WA	98201	2019	FORD	FUSION	Plug-in Hybrid Electric Vehicle (PHEV)	Not eligible due to low battery range	26	0	38.0	2006714	POIN (-122.2059 47.9765

In [6]:
```
data.shape
```
Out[6]:
```
(112634, 17)
```

In [7]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 112634 entries, 0 to 112633
Data columns (total 17 columns):
 #   Column                                             Non-Null Count   Dtype  
---  ------                                             --------------   -----  
 0   VIN (1-10)                                         112634 non-null  object 
 1   County                                             112634 non-null  object 
 2   City                                               112634 non-null  object 
 3   State                                              112634 non-null  object 
 4   Postal Code                                        112634 non-null  int64  
 5   Model Year                                         112634 non-null  int64  
 6   Make                                               112634 non-null  object 
 7   Model                                              112614 non-null  object 
 8   Electric Vehicle Type                              112634 non-null  object 
 9   Clean Alternative Fuel Vehicle (CAFV) Eligibility  112634 non-null  object 
 10  Electric Range                                     112634 non-null  int64  
 11  Base MSRP                                          112634 non-null  int64  
 12  Legislative District                               112348 non-null  float64
 13  DOL Vehicle ID                                     112634 non-null  int64  
 14  Vehicle Location                                   112610 non-null  object 
 15  Electric Utility                                   112191 non-null  object 
 16  2020 Census Tract                                  112634 non-null  int64  
dtypes: float64(1), int64(6), object(10)
memory usage: 14.6+ MB
```

In [8]:
```
data.columns
```

Out[8]:
```
Index(['VIN (1-10)', 'County', 'City', 'State', 'Postal 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', 'Electric Utility', '2020 Census Tract'],
      dtype='object')
```

In [9]:
```
# adjusting the dataset's column names
data.columns = data.columns.str.strip().str.lower().str.replace(' ', '_')
```

In [10]:
```
data.columns
```

Out[10]:
```
Index(['vin_(1-10)', 'county', 'city', 'state', 'postal_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', 'electric_utility', '2020_census_tract'],
      dtype='object')
```

In [11]:
```
# Checking for the null values in the dataset
data.isnull().sum().sort_values(ascending=False)/data.shape[0]*100
```

Out[11]:
```
electric_utility                                     0.393309
legislative_district                                 0.253920
vehicle_location                                     0.021308
model                                                0.017757
vin_(1-10)                                           0.000000
clean_alternative_fuel_vehicle_(cafv)_eligibility    0.000000
dol_vehicle_id                                       0.000000
base_msrp                                            0.000000
electric_range                                       0.000000
electric_vehicle_type                                0.000000
county                                               0.000000
make                                                 0.000000
model_year                                           0.000000
postal_code                                          0.000000
state                                                0.000000
city                                                 0.000000
2020_census_tract                                    0.000000
dtype: float64
```

Percentage of the null values in the columns, with respect to the entire records in the dataset is significantly very low. Hence removing the records with null values.

In [12]:
```
data.dropna(axis=0, inplace=True)
```

In [13]:
```
data.isnull().sum()
```

Out[13]:
```
vin_(1-10)                                           0
county                                               0
city                                                 0
state                                                0
postal_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                                 0
dol_vehicle_id                                       0
vehicle_location                                     0
electric_utility                                     0
2020_census_tract                                    0
dtype: int64
```

In [14]:
```
# Checking, if there are any duplicate rows in the dataset
print("There are {} duplicate entries in the datset".format(data.duplicated().sum()))
```

```
There are 0 duplicate entries in the datset
```

In [15]:
```
data['postal_code'] = data['postal_code'].astype('object')
```

In [16]:
```
data['postal_code'].dtype
```

Out[16]:
```
dtype('O')
```

In [17]:
```
data['model_year'] = data['model_year'].astype('object')
data.model_year.dtype
```

Out[17]:
```
dtype('O')
```

postal_code and model_year features are more suited to be categorical than numerical, hence changed the data type of both the features to 'object'

In [18]:
```
data['electric_range'].value_counts(normalize=True)*100
```

Out[18]:
```
electric_range
0      34.860725
215     5.601327
84      3.662886
220     3.577288
238     3.085990
          ...
11      0.002675
95      0.001783
57      0.000892
39      0.000892
59      0.000892
Name: proportion, Length: 101, dtype: float64
```

In [19]:
```
data['electric_range'].describe()
```

Out[19]:
```
count    112152.000000
mean         87.829651
std         102.336645
min           0.000000
25%           0.000000
50%          32.000000
75%         208.000000
max         337.000000
Name: electric_range, dtype: float64
```

In [20]:
```
electric_range_nonzero_median = data[data['electric_range'] > 0]['electric_range'].median()
electric_range_nonzero_median
```

Out[20]:
```
103.0
```

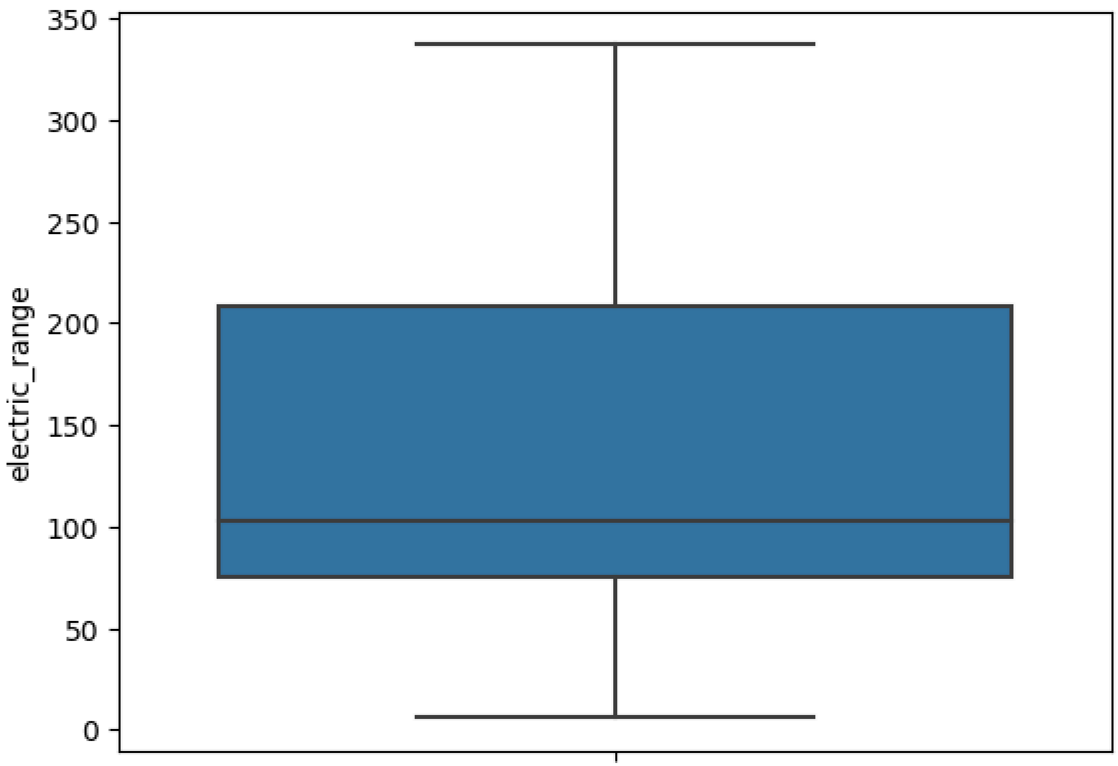
In [21]:
```
data['electric_range'].replace(to_replace=0, value=electric_range_nonzero_median, inplace=True)
```

In [22]:
```
data['electric_range'].describe()
```

Out[22]:
```
count    112152.000000
mean        123.736197
std          81.083472
min           6.000000
25%          75.000000
50%         103.000000
75%         208.000000
max         337.000000
Name: electric_range, dtype: float64
```

In [24]:
```
sns.boxplot(y=data['electric_range'])
```

Out[24]: <Axes: ylabel='electric_range'>



Since more than 34% of the values are 0, it doesn't make any sense to have 0 as the electric range for an electric vehicle. Replaced the 0 with non-zero median

In [25]:
```
data['base_msrp'].describe()
```

Out[25]:
```
count    112152.000000
mean       1793.882320
std       10785.259118
min           0.000000
25%           0.000000
50%           0.000000
75%           0.000000
max      845000.000000
Name: base_msrp, dtype: float64
```

In [26]:
```
data['base_msrp'].value_counts(normalize=True)*100
```

Out[26]:
```
base_msrp
0         96.881019
69900      1.331229
31950      0.362009
52900      0.189921
32250      0.140880
54950      0.120372
59900      0.119481
39995      0.105214
36900      0.089165
44100      0.084706
64950      0.073115
33950      0.069548
45600      0.067765
52650      0.059740
34995      0.051716
36800      0.044582
55700      0.041907
53400      0.024966
110950     0.021400
98950      0.020508
81100      0.016941
102000     0.016941
90700      0.016050
75095      0.014266
184400     0.010700
43700      0.008916
109000     0.006242
89100      0.006242
91250      0.003567
845000     0.000892
Name: proportion, dtype: float64
```

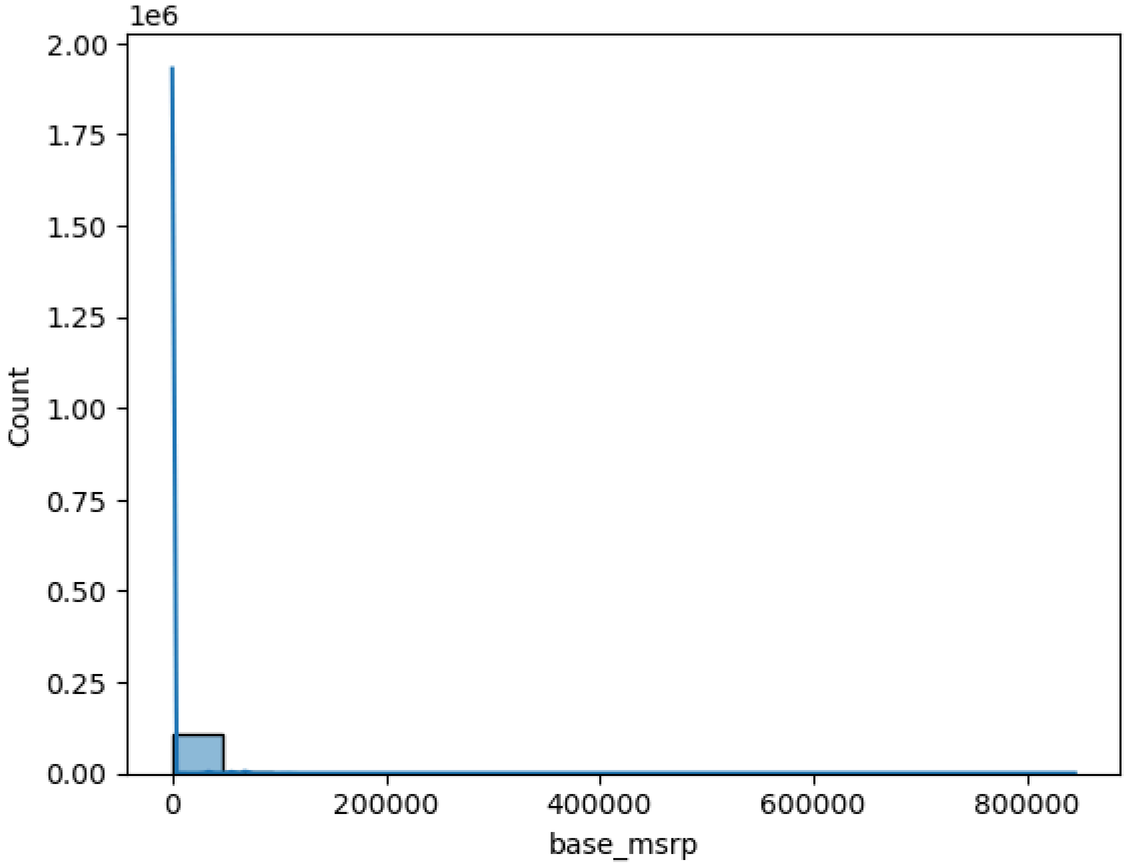
In [27]:
```
data[data['base_msrp'] > 0]['base_msrp'].value_counts(normalize=True)*100
```

Out[27]:

```
base_msrp
69900     42.681532
31950     11.606632
52900      6.089194
32250      4.516867
54950      3.859348
59900      3.830760
39995      3.373356
36900      2.858776
44100      2.715838
64950      2.344197
33950      2.229846
45600      2.172670
52650      1.915380
34995      1.658090
36800      1.429388
55700      1.343625
53400      0.800457
110950     0.686106
98950      0.657519
81100      0.543168
102000     0.543168
90700      0.514580
75095      0.457404
184400     0.343053
43700      0.285878
109000     0.200114
89100      0.200114
91250      0.114351
845000     0.028588
Name: proportion, dtype: float64
```

In [30]:

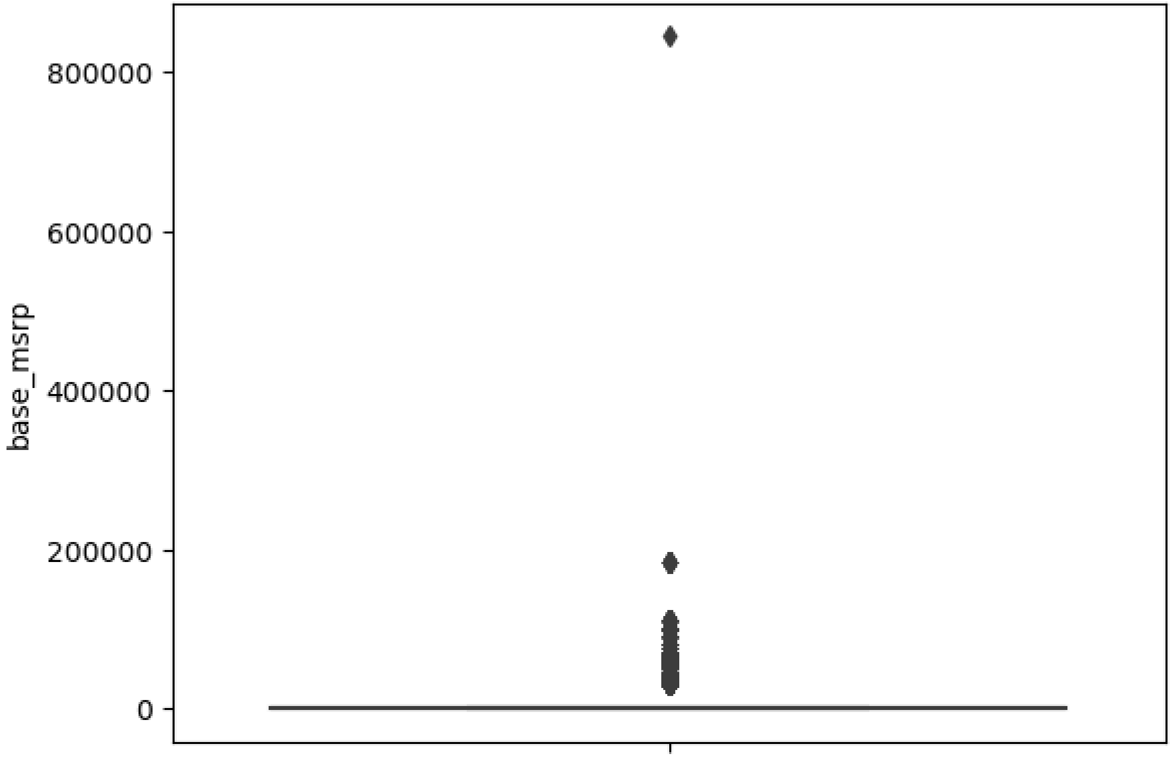
```
sns.histplot(data['base_msrp'], kde=True)
plt.show()

print(data['base_msrp'].describe())
```




```
count    112152.000000
mean       1793.882320
std       10785.259118
min           0.000000
25%           0.000000
50%           0.000000
75%           0.000000
max      845000.000000
Name: base_msrp, dtype: float64
```

In [32]:
```
sns.boxplot(y=data['base_msrp'])
```

Out[32]:
```
<Axes: ylabel='base_msrp'>
```



In [33]:
```
#Deleting the base_msrp feature as 97% of the values are 0
data.drop(columns='base_msrp', axis=1, inplace = True)
```

My justification to drop the base_msrp feature is, even if those values are replaced by mean or median or any other statistic. There will be no variablity in the data, as the percentage of the values which need to be replaced is very high.

In [34]:
```
np.sort(data['legislative_district'].unique())
```

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

In [35]:
```
# Converting data type to object
data['legislative_district'] = data['legislative_district'].astype('object')
data['legislative_district'].dtype
```

Out[35]:
```
dtype('O')
```

In [36]:
```
# No duplicate values in vehicle_id
data['dol_vehicle_id'].duplicated().sum()
```

Out[36]:
```
0
```

In [37]:
```
data['2020_census_tract'].value_counts()
```

Out[37]:
```
2020_census_tract
53033028500    583
53033032321    550
53033007800    418
53033024100    401
53033005600    394
              ...
53021020403      1
53021980100      1
53077001300      1
53077940007      1
53075000100      1
Name: count, Length: 1760, dtype: int64
```

In [38]:
```
# Converting the datatype to object
data['2020_census_tract'] = data['2020_census_tract'].astype('object')
data['2020_census_tract'].dtype
```

Out[38]:
```
dtype('O')
```

In [39]:
```
data.columns
```

Out[39]:
```
Index(['vin_(1-10)', 'county', 'city', 'state', 'postal_code', 'model_year',
       'make', 'model', 'electric_vehicle_type',
       'clean_alternative_fuel_vehicle_(cafv)_eligibility', 'electric_range',
       'legislative_district', 'dol_vehicle_id', 'vehicle_location',
       'electric_utility', '2020_census_tract'],
      dtype='object')
```

In [40]:
```
data['coordinates'] = data['vehicle_location'].str.removeprefix('POINT ').str.removeprefix('(').str.removesuffix(')').str.split('
```

In [41]:
```
data['latitude'] = data['coordinates'].apply(lambda x : x[0])
data['longitude'] = data['coordinates'].apply(lambda x : x[1])
```

In [42]:
```
data['latitude'].value_counts()
```

Out[42]:
```
latitude
-122.13158    2914
-122.2066     2059
-122.1872     2001
-122.31765    1878
-122.12096    1851
              ...
-121.59274       1
27.25316         1
-124.16705       1
-123.00026       1
-117.08742       1
Name: count, Length: 516, dtype: int64
```

In [43]:
```
data['longitude'].value_counts()
```

Out[43]:
```
longitude
47.67858    2914
47.67887    2059
47.61001    2001
47.70013    1878
47.55584    1851
            ...
48.48758       1
67.01865       1
47.11487       1
48.61989       1
46.53906       1
Name: count, Length: 516, dtype: int64
```

Univariate Analysis

Non_visual Univariate Analysis

In [44]:
```
numerical_df = data.select_dtypes(include=['int64', 'float64'])
numerical_df.head()
```

Out[44]:

	electric_range	dol_vehicle_id
2	73	218972519
3	238	186750406
4	26	2006714
5	215	475635324
6	75	253546023

In [45]:

```
# numerical_univariate_analysis function
def numerical_univariate_analysis(num_df):
    for column_name in num_df:
        print("*"*10, column_name, "*"*10)
        print(num_df[column_name].describe())
        print()
```

In [46]:

```
numerical_univariate_analysis(numerical_df)
```

```
********** electric_range **********
count    112152.000000
mean        123.736197
std          81.083472
min           6.000000
25%          75.000000
50%         103.000000
75%         208.000000
max         337.000000
Name: electric_range, dtype: float64

********** dol_vehicle_id **********
count    1.121520e+05
mean     1.994712e+08
std      9.401842e+07
min      4.777000e+03
25%      1.484164e+08
50%      1.923916e+08
75%      2.191885e+08
max      4.792548e+08
Name: dol_vehicle_id, dtype: float64
```

In [47]:
```
data.select_dtypes(include='object').columns
```

Out[47]:
```
Index(['vin_(1-10)', 'county', 'city', 'state', 'postal_code', 'model_year',
       'make', 'model', 'electric_vehicle_type',
       'clean_alternative_fuel_vehicle_(cafv)_eligibility',
       'legislative_district', 'vehicle_location', 'electric_utility',
       '2020_census_tract', 'coordinates', 'latitude', 'longitude'],
      dtype='object')
```

In [48]:
```
discrete_columns = ['vin_(1-10)', 'county', 'city', 'state', 'postal_code', 'model_year',
       'make', 'model', 'electric_vehicle_type',
       'clean_alternative_fuel_vehicle_(cafv)_eligibility',
       'legislative_district', 'electric_utility',
       '2020_census_tract']
```

In [49]:
```
discrete_df = data[discrete_columns]
discrete_df.head()
```

Out[49]:

	vin_(1-10)	county	city	state	postal_code	model_year	make	model	electric_vehicle_type	clean_alternative_fuel_vehicle_(cafv)_eligil
2	JN1AZ0CP8B	Yakima	Yakima	WA	98901	2011	NISSAN	LEAF	Battery Electric Vehicle (BEV)	Clean Alternative Fuel Vehicle Eli
3	1G1FW6S08H	Skagit	Concrete	WA	98237	2017	CHEVROLET	BOLT EV	Battery Electric Vehicle (BEV)	Clean Alternative Fuel Vehicle Eli
4	3FA6P0SU1K	Snohomish	Everett	WA	98201	2019	FORD	FUSION	Plug-in Hybrid Electric Vehicle (PHEV)	Not eligible due to low battery r
5	5YJ3E1EB5J	Snohomish	Bothell	WA	98021	2018	TESLA	MODEL 3	Battery Electric Vehicle (BEV)	Clean Alternative Fuel Vehicle Eli
6	1N4AZ0CP4D	Snohomish	Everett	WA	98203	2013	NISSAN	LEAF	Battery Electric Vehicle (BEV)	Clean Alternative Fuel Vehicle Eli

In [50]:
```
# discrete_univariate_analysis function

def discrete_univariate_analysis(discrete_df):
```

```
    for column_name in discrete_df:
        print("*"*10, column_name, "*"*10)
        print(discrete_df[column_name].agg(['count', 'nunique', 'unique']))
        print('Value Counts: \n', discrete_df[column_name].value_counts())
        print()
```

In [51]:
```
discrete_univariate_analysis(discrete_df)
```

```
********** vin_(1-10) **********
count                                                     112152
nunique                                                     7522
unique     [JN1AZ0CP8B, 1G1FW6S08H, 3FA6P0SU1K, 5YJ3E1EB5...
Name: vin_(1-10), dtype: object
Value Counts:
 vin_(1-10)
5YJYGDEE9M    471
5YJYGDEE0M    463
5YJYGDEE7M    447
5YJYGDEE8M    446
5YJYGDEE2M    435
             ...
YV4BR0DL8M      1
JTJHKCFZ5N      1
WA1J2BFZ3N      1
KNDC4DLC5P      1
WA1LAAGE5M      1
Name: count, Length: 7522, dtype: int64

********** county **********
count                                                     112152
nunique                                                       39
unique     [Yakima, Skagit, Snohomish, Island, Thurston, ...
Name: county, dtype: object
Value Counts:
 county
King            58980
Snohomish       12412
Pierce           8525
Clark            6681
Thurston         4109
Kitsap           3828
Whatcom          2839
Spokane          2785
Benton           1376
Island           1298
Skagit           1228
Clallam           728
San Juan          717
Jefferson         698
Chelan            654
Yakima            617
Cowlitz           569
```

```
Mason            547
Lewis            431
Grays Harbor     402
Kittitas         392
Franklin         365
Grant            335
Walla Walla      312
Douglas          221
Whitman          177
Klickitat        175
Okanogan         149
Pacific          145
Skamania         139
Stevens           91
Asotin            48
Wahkiakum         39
Adams             34
Pend Oreille      32
Lincoln           30
Ferry             27
Columbia          13
Garfield           4
Name: count, dtype: int64

********** city **********
count                                                 112152
nunique                                                  435
unique     [Yakima, Concrete, Everett, Bothell, Mukilteo,...
Name: city, dtype: object
Value Counts:
 city
Seattle           20295
Bellevue           5919
Redmond            4199
Vancouver          4013
Kirkland           3598
                  ...
Walla Walla Co        1
Clallam Bay           1
Malott                1
Rockport              1
Uniontown             1
Name: count, Length: 435, dtype: int64
```

```
********** state **********
count      112152
nunique         1
unique       [WA]
Name: state, dtype: object
Value Counts:
 state
WA    112152
Name: count, dtype: int64

********** postal_code **********
count                                                  112152
nunique                                                   516
unique     [98901, 98237, 98201, 98021, 98203, 98275, 982...
Name: postal_code, dtype: object
Value Counts:
 postal_code
98052    2914
98033    2059
98004    2001
98115    1878
98006    1851
         ... 
98283       1
98530       1
98535       1
98243       1
99179       1
Name: count, Length: 516, dtype: int64

********** model_year **********
count                                                  112152
nunique                                                    20
unique     [2011, 2017, 2019, 2018, 2013, 2016, 2020, 202...
Name: model_year, dtype: object
Value Counts:
 model_year
2022    26455
2021    18277
2018    14190
2020    10998
2019    10216
2017     8598
2016     5709
```

```
2015     4918
2013     4669
2014     3665
2023     1863
2012     1695
2011      835
2010       24
2008       23
2000       10
1999        3
2002        2
1997        1
1998        1
Name: count, dtype: int64

********** make **********
count                                                 112152
nunique                                                   34
unique     [NISSAN, CHEVROLET, FORD, TESLA, KIA, AUDI, BM...
Name: make, dtype: object
Value Counts:
 make
TESLA            51883
NISSAN           12846
CHEVROLET        10140
FORD              5780
BMW               4660
KIA               4469
TOYOTA            4368
VOLKSWAGEN        2507
AUDI              2320
VOLVO             2256
CHRYSLER          1780
HYUNDAI           1407
JEEP              1143
RIVIAN             883
FIAT               820
PORSCHE            817
HONDA              788
MINI               631
MITSUBISHI         585
POLESTAR           557
MERCEDES-BENZ      503
SMART              271
```

```
JAGUAR              218
LINCOLN             167
CADILLAC            108
LUCID MOTORS         65
SUBARU               59
LAND ROVER           38
LEXUS                33
FISKER               19
GENESIS              18
AZURE DYNAMICS        7
TH!NK                 3
BENTLEY               3
Name: count, dtype: int64

********** model **********
count                                                  112152
nunique                                                   114
unique     [LEAF, BOLT EV, FUSION, MODEL 3, SOUL, Q5 E, M...
Name: model, dtype: object
Value Counts:
 model
MODEL 3        23042
MODEL Y        17086
LEAF           12846
MODEL S         7346
BOLT EV         4895
               ...
745LE              2
S-10 PICKUP        1
SOLTERRA           1
918                1
FLYING SPUR        1
Name: count, Length: 114, dtype: int64

********** electric_vehicle_type **********
count                                                  112152
nunique                                                     2
unique     [Battery Electric Vehicle (BEV), Plug-in Hybri...
Name: electric_vehicle_type, dtype: object
Value Counts:
 electric_vehicle_type
Battery Electric Vehicle (BEV)            85732
Plug-in Hybrid Electric Vehicle (PHEV)    26420
Name: count, dtype: int64
```

```
********** clean_alternative_fuel_vehicle_(cafv)_eligibility **********
count                                                     112152
nunique                                                        3
unique     [Clean Alternative Fuel Vehicle Eligible, Not ...
Name: clean_alternative_fuel_vehicle_(cafv)_eligibility, dtype: object
Value Counts:
 clean_alternative_fuel_vehicle_(cafv)_eligibility
Clean Alternative Fuel Vehicle Eligible                          58395
Eligibility unknown as battery range has not been researched    39097
Not eligible due to low battery range                            14660
Name: count, dtype: int64

********** legislative_district **********
count                                                     112152
nunique                                                       49
unique     [15.0, 39.0, 38.0, 1.0, 21.0, 10.0, 40.0, 22.0...
Name: legislative_district, dtype: object
Value Counts:
 legislative_district
41.0    7602
45.0    7112
48.0    6460
36.0    5251
46.0    4721
1.0     4714
5.0     4691
43.0    4620
37.0    3554
34.0    3477
18.0    3024
22.0    2772
32.0    2707
11.0    2702
44.0    2670
23.0    2614
21.0    2613
40.0    2599
26.0    2260
33.0    2112
10.0    2051
31.0    1908
17.0    1907
47.0    1875
```

```
24.0    1661
27.0    1651
42.0    1625
35.0    1613
39.0    1574
49.0    1573
28.0    1447
30.0    1267
2.0     1225
8.0     1157
38.0    1065
25.0    1049
6.0     1041
12.0    1004
20.0     973
4.0      845
13.0     748
14.0     720
29.0     692
19.0     669
16.0     611
9.0      606
3.0      557
7.0      486
15.0     277
Name: count, dtype: int64

********** electric_utility **********
count                                                 112152
nunique                                                   73
unique     [PACIFICORP, PUGET SOUND ENERGY INC, PUD NO 2 ...
Name: electric_utility, dtype: object
Value Counts:
 electric_utility
PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)                                    40231
PUGET SOUND ENERGY INC                                                           22166
CITY OF SEATTLE - (WA)|CITY OF TACOMA - (WA)                                     21439
BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF CLARK COUNTY - (WA)                  6522
BONNEVILLE POWER ADMINISTRATION||CITY OF TACOMA - (WA)||PENINSULA LIGHT COMPANY   5049
                                                                                 ...
BONNEVILLE POWER ADMINISTRATION||PENINSULA LIGHT COMPANY                             1
BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF ASOTIN COUNTY                           1
CITY OF SEATTLE - (WA)                                                               1
BONNEVILLE POWER ADMINISTRATION||NESPELEM VALLEY ELEC COOP, INC                      1
```

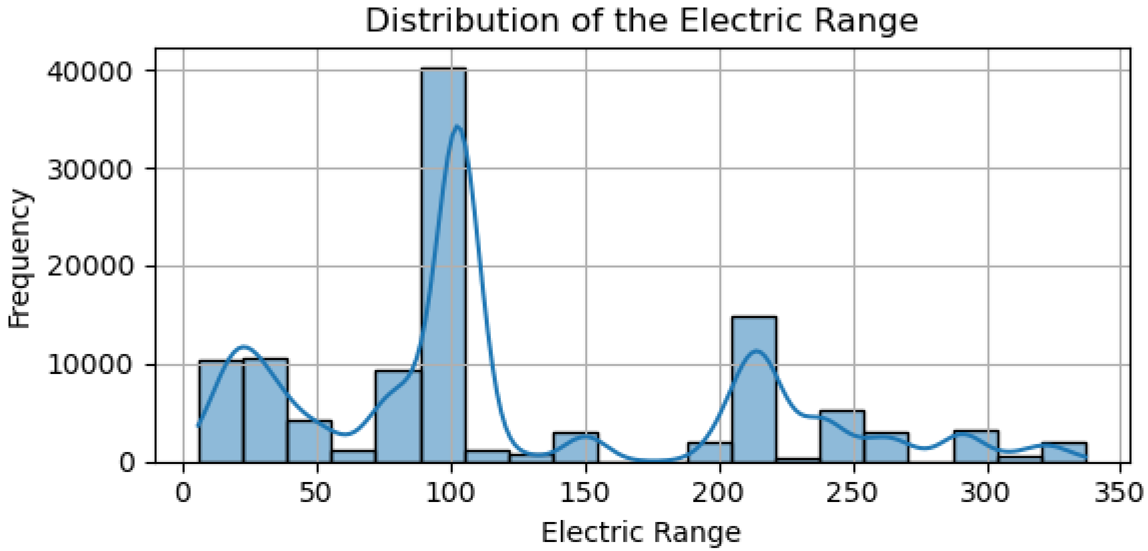
```
BONNEVILLE POWER ADMINISTRATION||PUD NO 1 OF CLALLAM COUNTY|PUD NO 1 OF JEFFERSON COUNTY        1
Name: count, Length: 73, dtype: int64

********** 2020_census_tract **********
count                                                         112152
nunique                                                         1760
unique     [53077001602, 53057951101, 53061041500, 530610...
Name: 2020_census_tract, dtype: object
Value Counts:
 2020_census_tract
53033028500    583
53033032321    550
53033007800    418
53033024100    401
53033005600    394
              ...
53021020403      1
53021980100      1
53077001300      1
53077940007      1
53075000100      1
Name: count, Length: 1760, dtype: int64
```

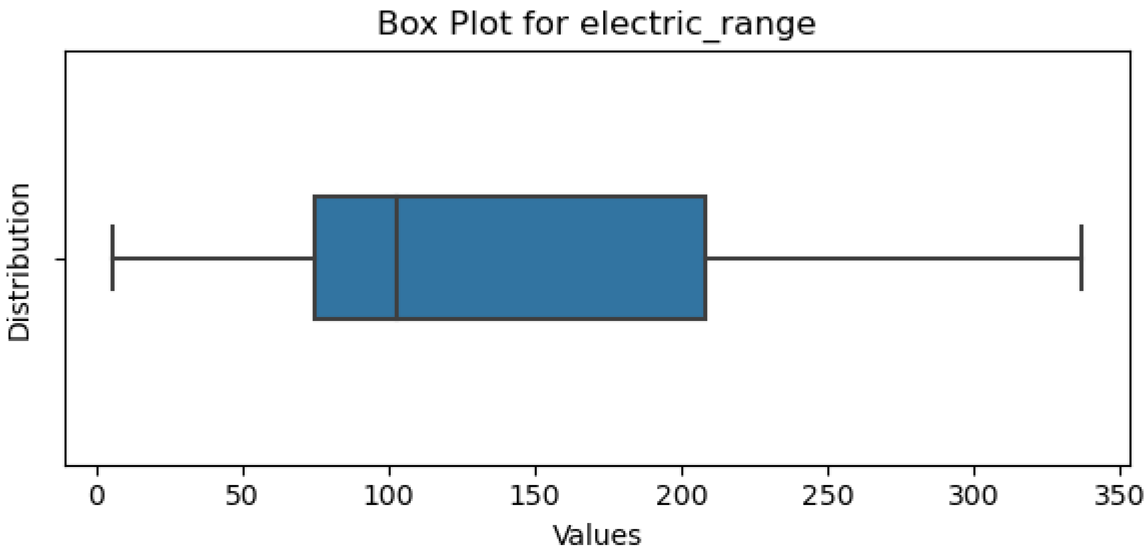
Univariate - Visual Analysis

1. Distribution of Electric Range

In [52]:
```
# Hiatogram
plt.figure(figsize=(6,3))
sns.histplot(data['electric_range'],bins=20, kde=True,edgecolor='black')
plt.title('Distribution of the Electric Range')
plt.xlabel('Electric Range')
plt.ylabel('Frequency')
plt.grid(True)
plt.tight_layout()
plt.show()

# Box Plot
plt.figure(figsize=(6, 3))
sns.boxplot(x = data['electric_range'], width=0.3, fliersize=5)
```

```
plt.title('Box Plot for electric_range')
plt.xlabel('Values')
plt.ylabel('Distribution')
plt.tight_layout()
plt.show()
```





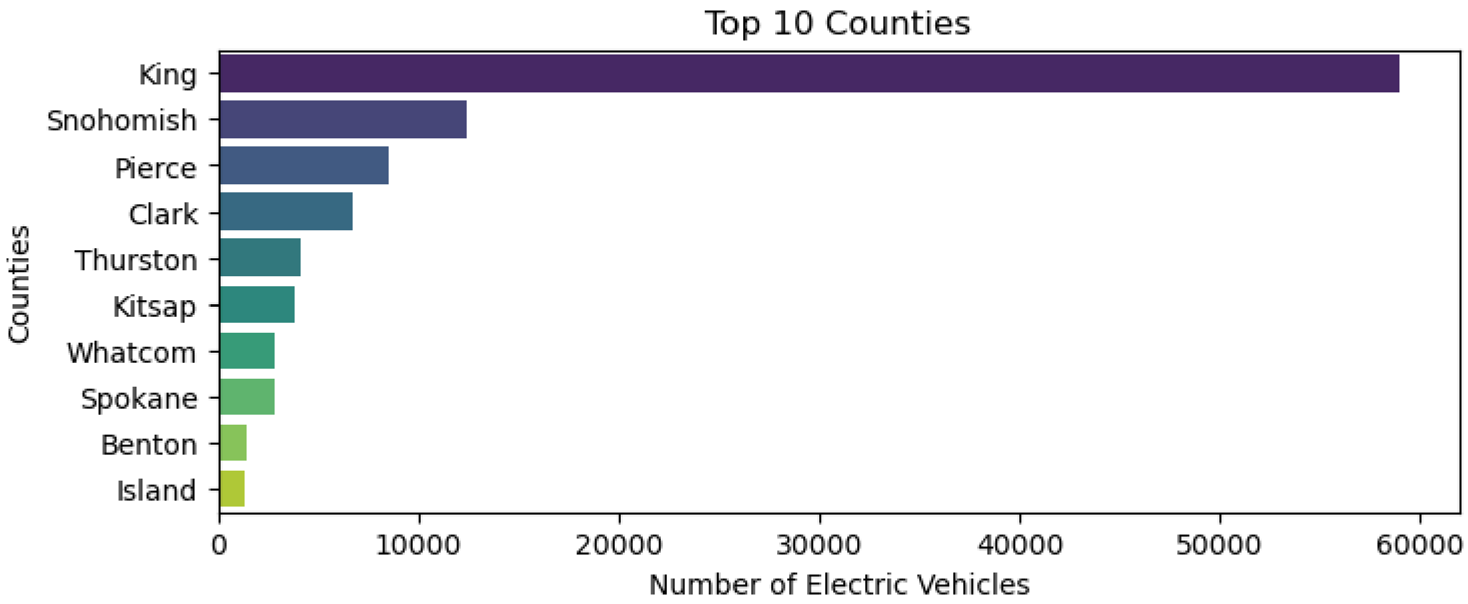
There are no outliers observed in the electric range column. NOt many vehicles have more range.

1. Top 10 Counties W.R.T number of electric vehicles

In [53]:
```
top_10_counties = data['county'].value_counts().head(10)
top_10_counties
```

Out[53]:
```
county
King          58980
Snohomish     12412
Pierce         8525
Clark          6681
Thurston       4109
Kitsap         3828
Whatcom        2839
Spokane        2785
Benton         1376
Island         1298
Name: count, dtype: int64
```

In [54]:
```
plt.figure(figsize=(8,3))
sns.barplot(x=top_10_counties.values, y=top_10_counties.index, palette='viridis')
plt.title("Top 10 Counties")
plt.xlabel("Number of Electric Vehicles")
plt.ylabel("Counties")
plt.show()
```



It can be observed that 'King' is top county having more number of electric vehicles, followed by Snohomish and Pierce. 10th county is ISland

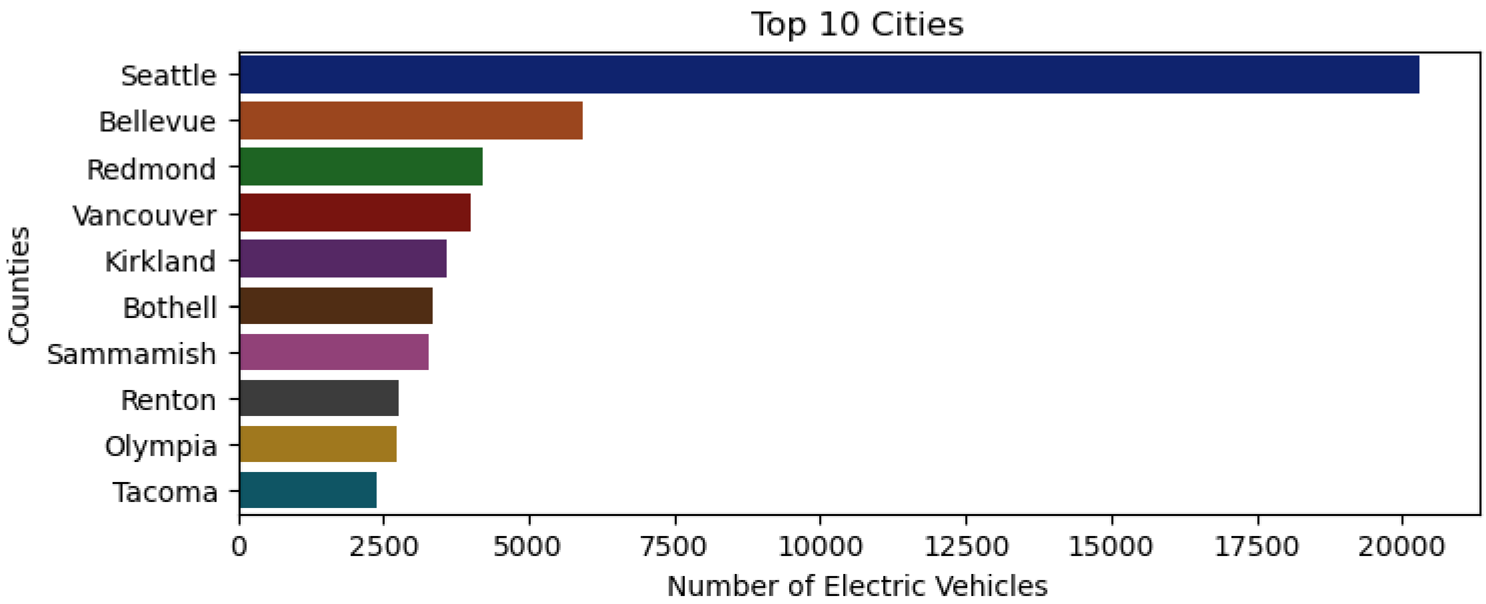
1. Top 10 Cities

In [55]:
```
top_10_cities = data['city'].value_counts().head(10)
top_10_cities
```

Out[55]:
```
city
Seattle      20295
Bellevue      5919
Redmond       4199
Vancouver     4013
Kirkland      3598
Bothell       3334
Sammamish     3291
Renton        2777
Olympia       2729
Tacoma        2375
Name: count, dtype: int64
```

In [56]:
```
plt.figure(figsize=(8,3))
sns.barplot(x=top_10_cities.values, y=top_10_cities.index, palette='dark')
```

```
plt.title("Top 10 Cities")
plt.xlabel("Number of Electric Vehicles")
plt.ylabel("Counties")
plt.show()
```



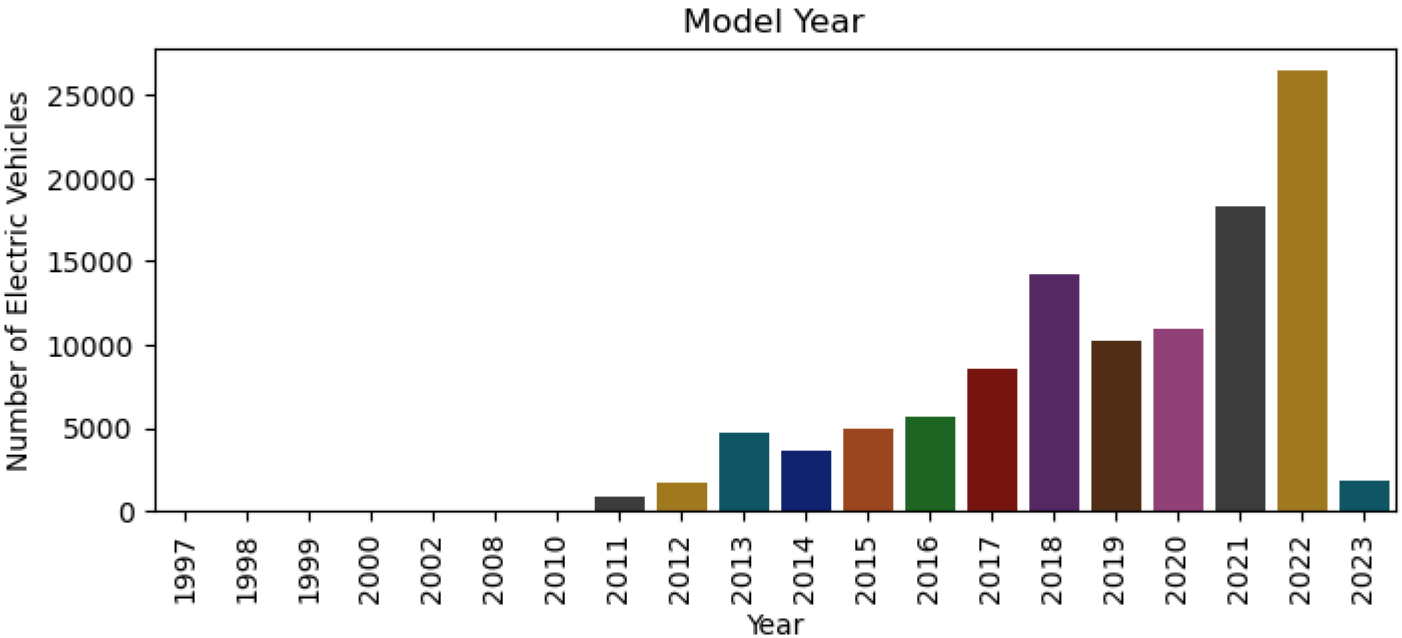
'Seattle' is top city having more number of electric vehicles, followed by Bellevue and Redmond. 10th county is Tacoma

1. Model Year

In [57]:
```
model_year = data['model_year'].value_counts()
model_year
```

Out[57]:
```
model_year
2022    26455
2021    18277
2018    14190
2020    10998
2019    10216
2017     8598
2016     5709
2015     4918
2013     4669
2014     3665
2023     1863
2012     1695
2011      835
2010       24
2008       23
2000       10
1999        3
2002        2
1997        1
1998        1
Name: count, dtype: int64
```

In [62]:
```
plt.figure(figsize=(8,3))
sns.barplot(x=model_year.index, y=model_year.values, palette='dark')
plt.title("Model Year")
plt.xlabel("Year")
plt.ylabel("Number of Electric Vehicles")
plt.xticks(rotation=90)
plt.show()
```



More Electric vehicles have been manufactures in 2022, followed by 2021 and 2018. Least being 2011. Significant increase in the manufacturing of the electric vehicles can be observed over the years.

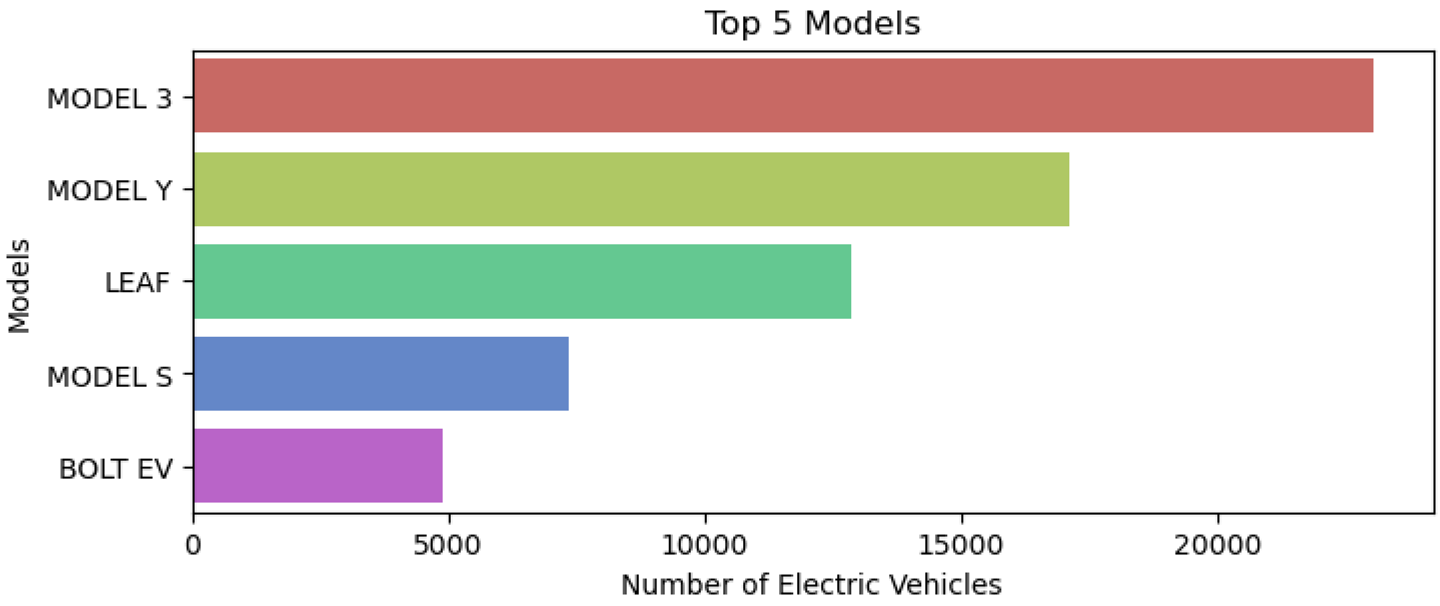
1. Top 5 Models

In [63]:
```
top5_models = data['model'].value_counts().head(5)
top5_models
```

Out[63]:
```
model
MODEL 3    23042
MODEL Y    17086
LEAF       12846
MODEL S     7346
BOLT EV     4895
Name: count, dtype: int64
```

In [64]:
```
plt.figure(figsize=(8,3))
sns.barplot(x=top5_models.values, y=top5_models.index, palette='hls')
plt.title("Top 5 Models")
plt.xlabel("Number of Electric Vehicles")
```

```
plt.ylabel("Models")
plt.show()
```



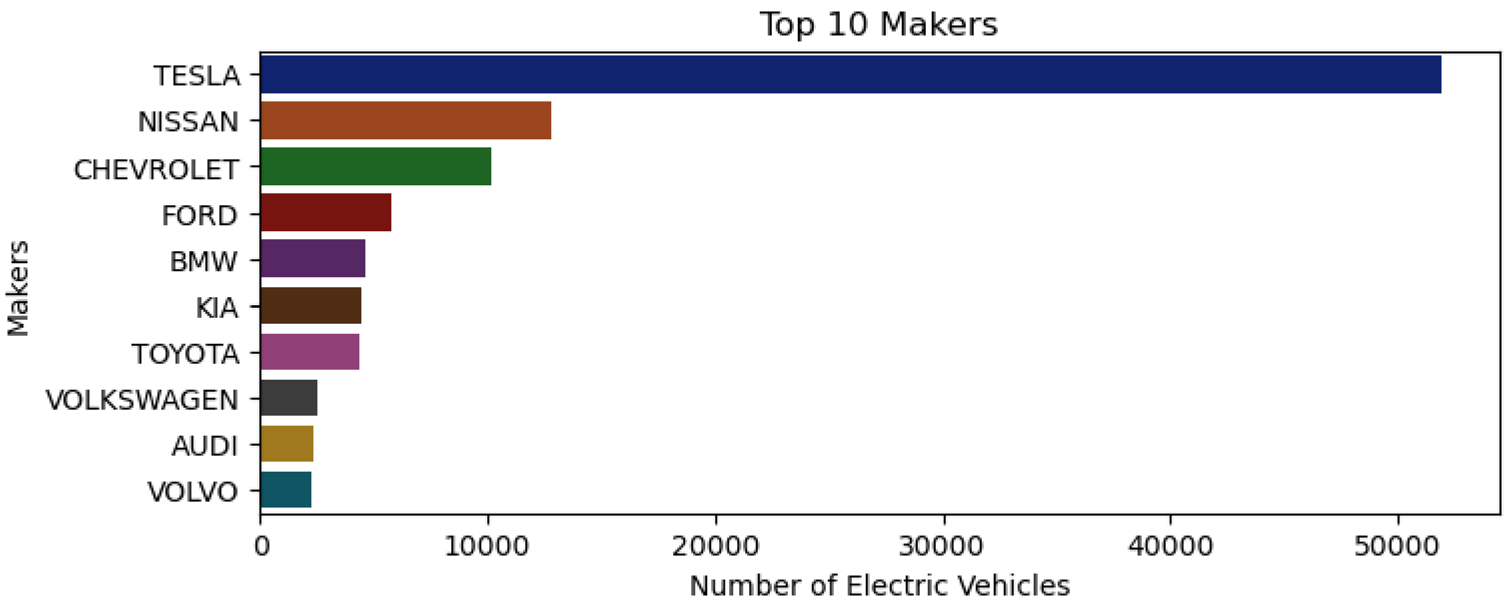
There more Model 3 electric vehicles followed by Model Y in top 5.

1. Top 10 makers

In [65]:
```
top_10_makers = data['make'].value_counts().head(10)
top_10_makers
```

Out[65]:
```
make
TESLA         51883
NISSAN        12846
CHEVROLET     10140
FORD           5780
BMW            4660
KIA            4469
TOYOTA         4368
VOLKSWAGEN     2507
AUDI           2320
VOLVO          2256
Name: count, dtype: int64
```

In [66]:
```
plt.figure(figsize=(8,3))
sns.barplot(x=top_10_makers.values, y=top_10_makers.index, palette='dark')
plt.title("Top 10 Makers")
plt.xlabel("Number of Electric Vehicles")
plt.ylabel("Makers")
plt.show()
```



Telsa makes, highest number of electric vehicles followed by Nissan and 10th being Volvo

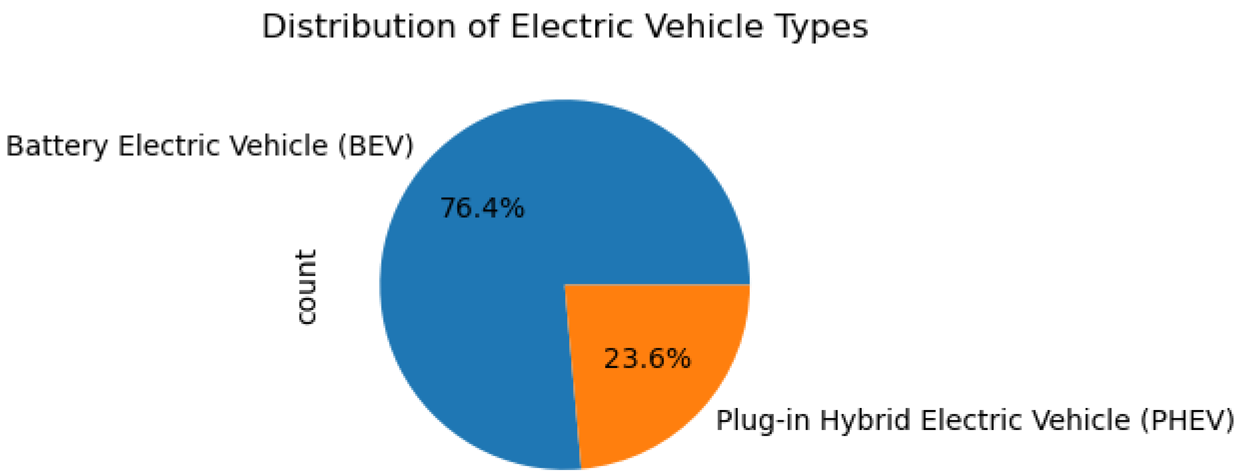
1. Electric Vehicle Type

In [67]:
```
data['electric_vehicle_type'].value_counts(normalize=True)
```

Out[67]:
```
electric_vehicle_type
Battery Electric Vehicle (BEV)            0.764427
Plug-in Hybrid Electric Vehicle (PHEV)    0.235573
Name: proportion, dtype: float64
```

In [68]:
```
plt.figure(figsize=(6,3))
data['electric_vehicle_type'].value_counts().plot(kind='pie', autopct='%1.1f%%')
```

```
plt.title('Distribution of Electric Vehicle Types')
plt.show()
```



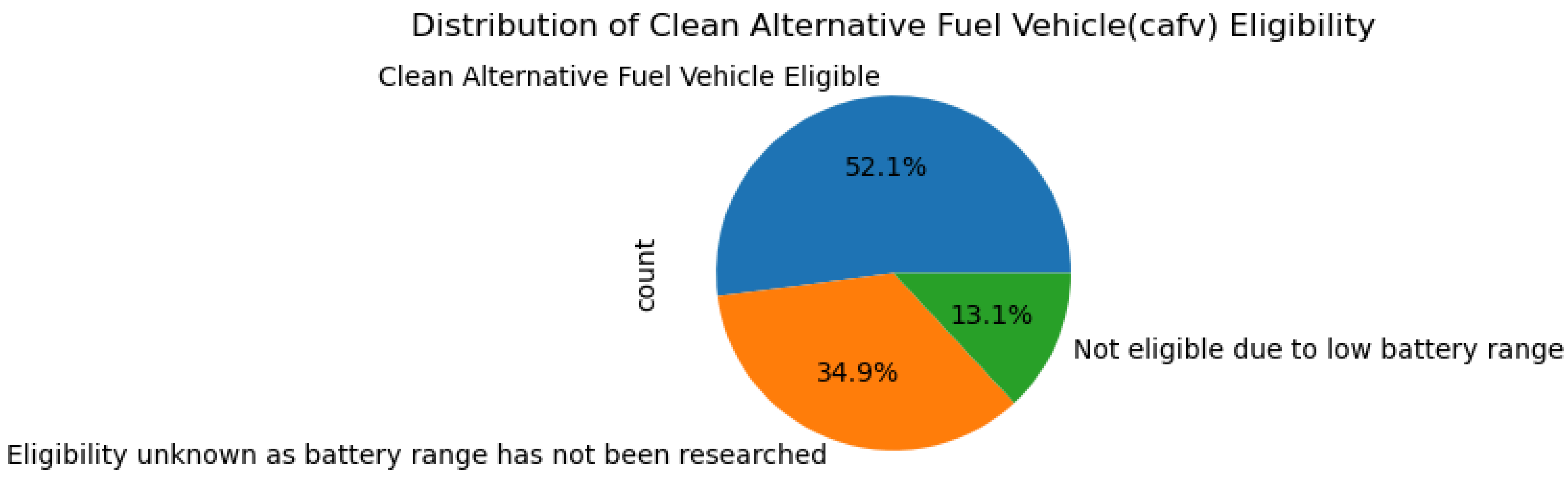
There Seems to be more Battery Vehicles than Hybrid vehicles in the market.

1. Clean Alternative Fuel Vehicle(cafv) Eligibility

In [69]:
```
data['clean_alternative_fuel_vehicle_(cafv)_eligibility'].value_counts(normalize=True)*100
```

Out[69]:
```
clean_alternative_fuel_vehicle_(cafv)_eligibility
Clean Alternative Fuel Vehicle Eligible                          52.067730
Eligibility unknown as battery range has not been researched    34.860725
Not eligible due to low battery range                            13.071546
Name: proportion, dtype: float64
```

In [70]:
```
plt.figure(figsize=(6,3))
data['clean_alternative_fuel_vehicle_(cafv)_eligibility'].value_counts().plot(kind='pie', autopct='%1.1f%%')
plt.title('Distribution of Clean Alternative Fuel Vehicle(cafv) Eligibility')
plt.show()
```



Approximately 52% of the vehicles are eligible for Clean Alternative Fuel Vehicle incentives.

Bivariate Analysis

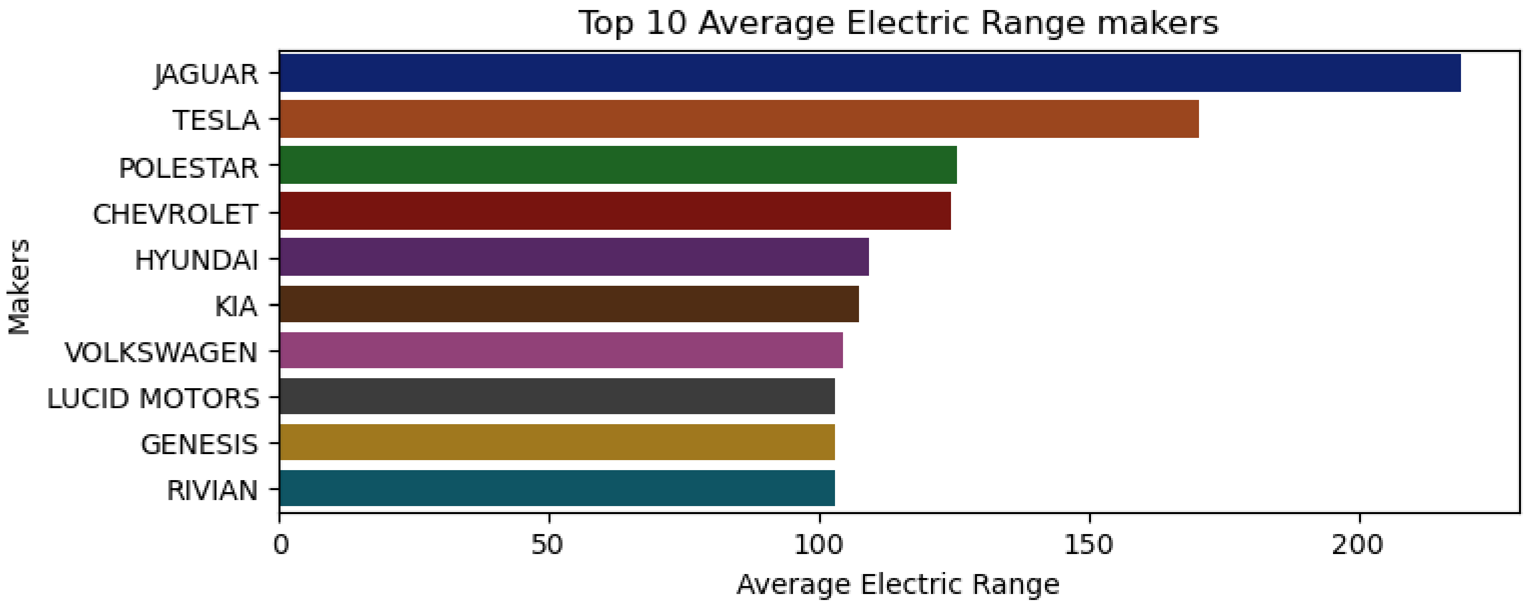
Categorical vs Numerical

1. Electric_range vs Make

In [71]:
```
make_er_diff = data.groupby('make')['electric_range'].mean().sort_values(ascending=False).head(10)
make_er_diff
```

Out[71]:
```
make
JAGUAR          218.977064
TESLA           170.465894
POLESTAR        125.639138
CHEVROLET       124.499408
HYUNDAI         109.249467
KIA             107.441262
VOLKSWAGEN      104.607499
LUCID MOTORS    103.000000
GENESIS         103.000000
RIVIAN          103.000000
Name: electric_range, dtype: float64
```

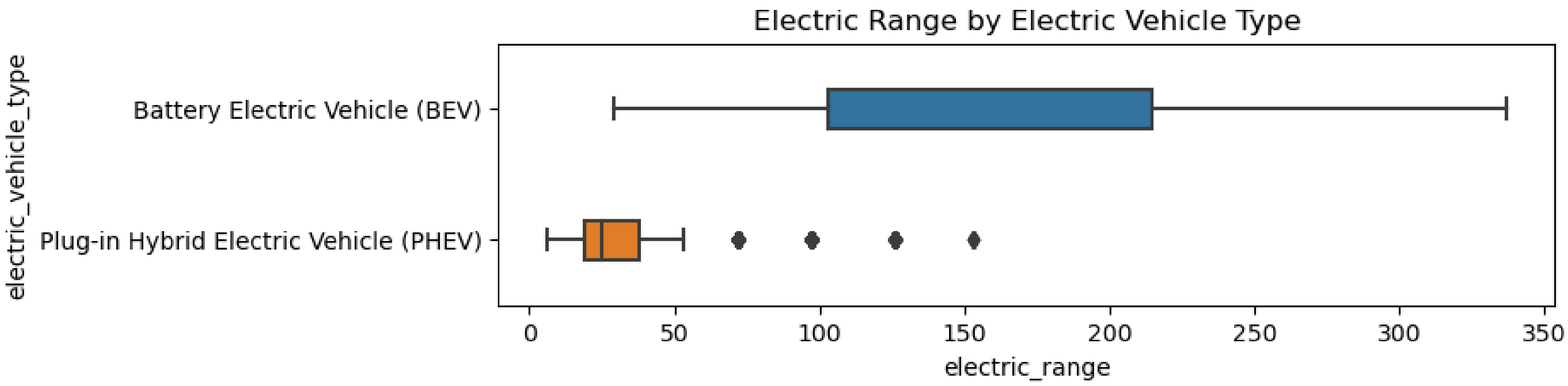
In [72]:
```python
plt.figure(figsize=(8,3))
sns.barplot(x=make_er_diff.values, y=make_er_diff.index, palette='dark')
plt.title("Top 10 Average Electric Range makers")
plt.xlabel("Average Electric Range")
plt.ylabel("Makers")
plt.show()
```



On an average 'Jaguar' makes the vehicles with highest electric range, followed by 'Tesla' and 'Polestar'. 10th being 'Genesis'

2. Electric Range vs Electric Vehicle Type

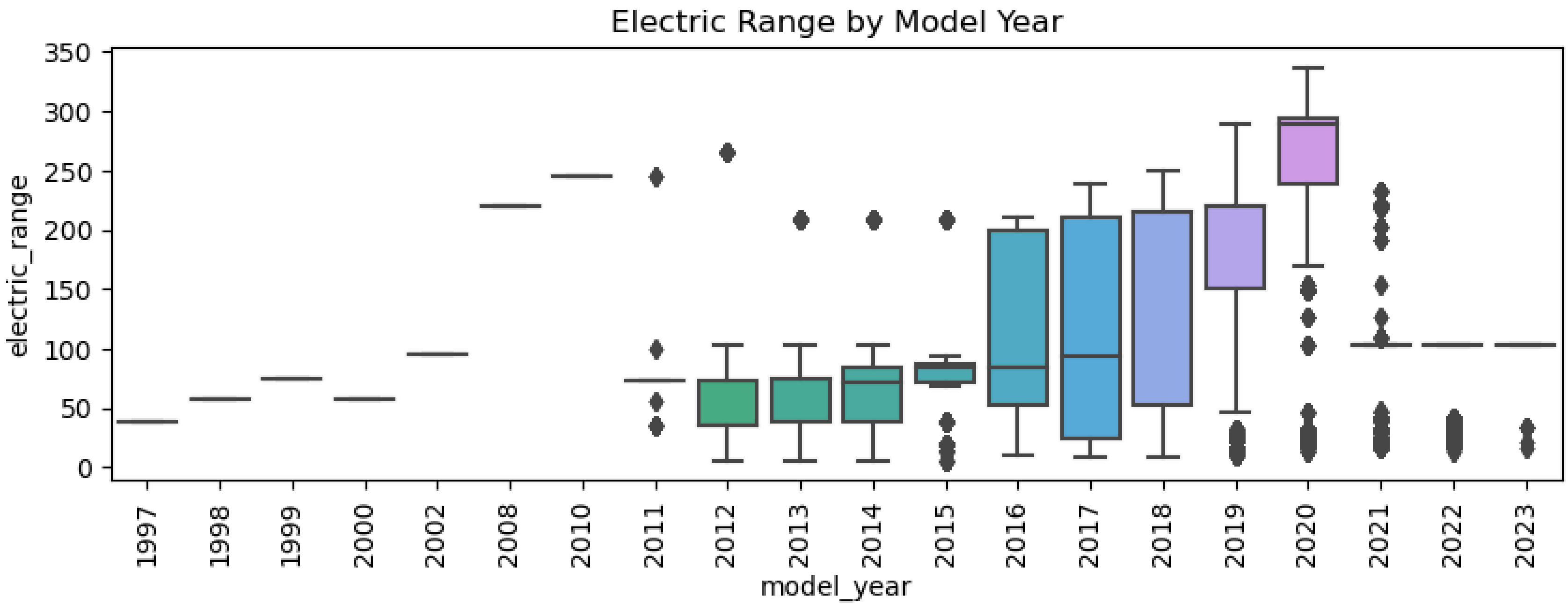
In [73]:
```
plt.figure(figsize=(8,2))
sns.boxplot(x='electric_range', y='electric_vehicle_type', data=data, width=0.3, fliersize=5)
plt.title('Electric Range by Electric Vehicle Type')
plt.show()
```



It is evident that on an average or overall, Battery vehicles have more electric range than hybrid vehicles

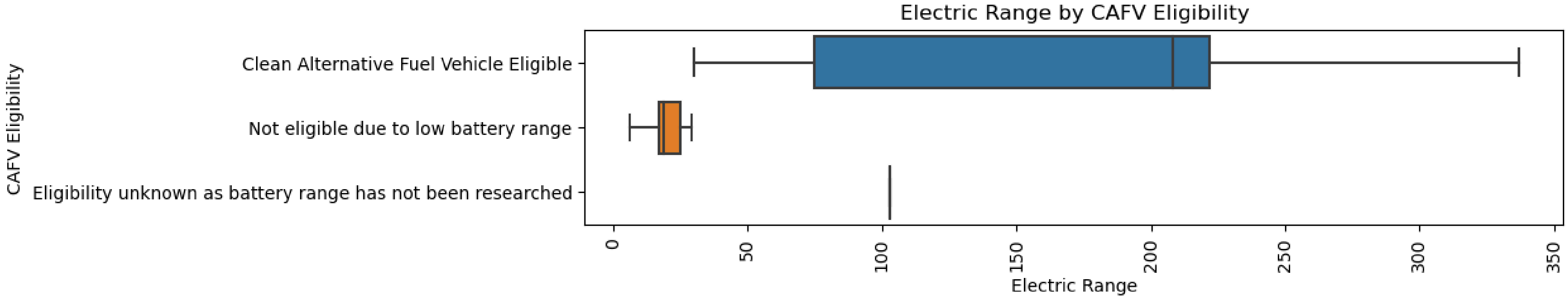
3. Model Year vs Electric Range

In [74]:
```
# Boxplot to analyze electric range by model year
plt.figure(figsize=(10,3))
sns.boxplot(x='model_year', y='electric_range', data=data)
plt.title('Electric Range by Model Year')
plt.xticks(rotation=90)
plt.show()
```



4. Electric Range vs Clean_alternative_fuel*vehicle*(cafv)_eligibility

In [75]:
```
plt.figure(figsize=(10,2))
sns.boxplot(y='clean_alternative_fuel_vehicle_(cafv)_eligibility', x='electric_range', data=data)
plt.title('Electric Range by CAFV Eligibility')
plt.xlabel('Electric Range')
plt.ylabel('CAFV Eligibility')
plt.xticks(rotation=90)
plt.show()
```



It is clearly observable that, the vehicles eligible for Clean Alternative Fuel incentives is having the varied eletric range, which tells that there has been significant increase in the range for these vehicles, which helps them to get eligible for this incentive.

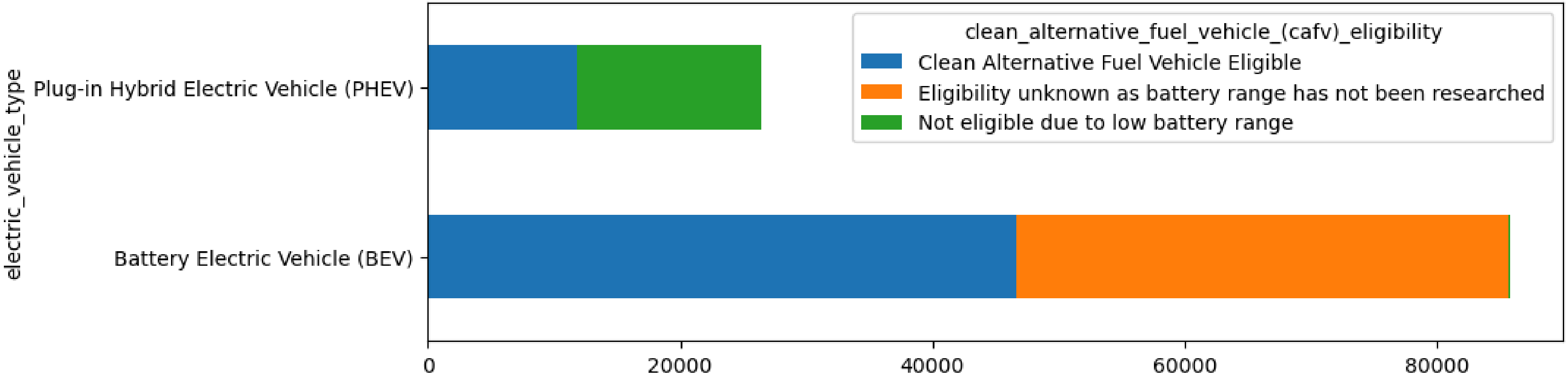
other two categories clearly shows there is no variablity in electric range at all.

Categorical vs categorical

1. Electric_vehicle_type vs Clean_alternative_fuel*vehicle*(cafv)_eligibility

In [76]:
```
pd.crosstab(data['electric_vehicle_type'], data['clean_alternative_fuel_vehicle_(cafv)_eligibility']).plot(kind='barh', figsize=(
```

Out[76]: <Axes: ylabel='electric_vehicle_type'>



In [77]:
```
pd.crosstab(data['electric_vehicle_type'], data['clean_alternative_fuel_vehicle_(cafv)_eligibility'])
```

Out[77]:

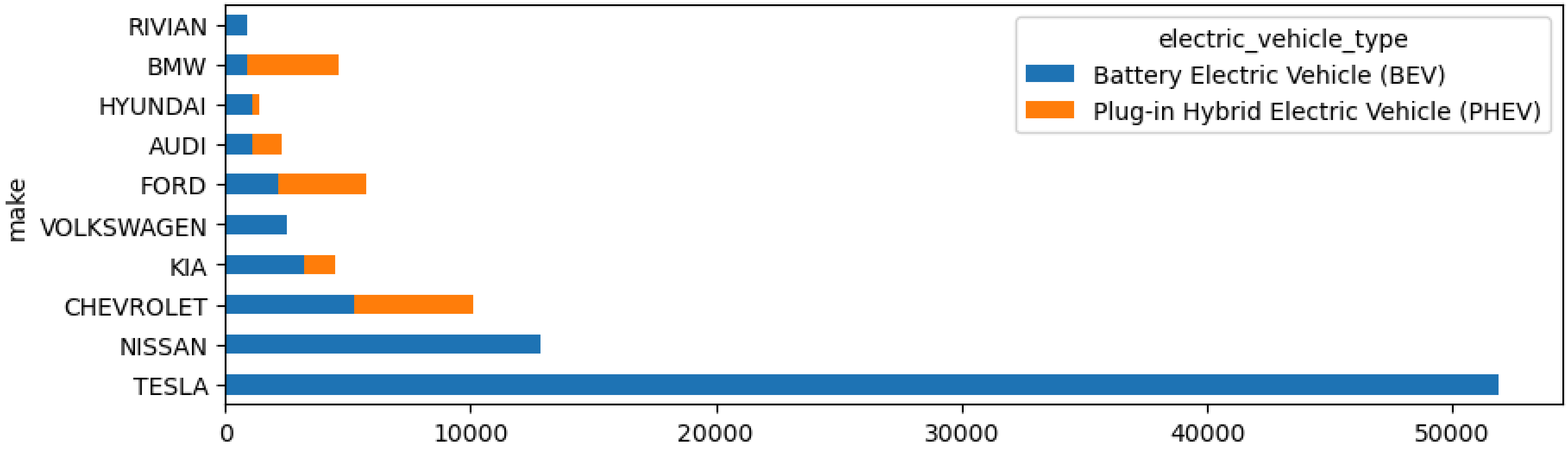
clean_alternative_fuel_vehicle_(cafv)_eligibility	Clean Alternative Fuel Vehicle Eligible	Eligibility unknown as battery range has not been researched	Not eligible due to low battery range
electric_vehicle_type			
Battery Electric Vehicle (BEV)	46626	39097	9
Plug-in Hybrid Electric Vehicle (PHEV)	11769	0	14651

1. Both Battery and Hybrid vehicles are eliugible for CAFV incentive. The number is more for Battery vehicles.
2. Hybrid models have more vehicles with low battery.

2. Make vs Electric Vehicle Type

In [78]:
```
crosstab_result = pd.crosstab(data['make'], data['electric_vehicle_type'])
sorted_crosstab = crosstab_result.sort_values(by=['Battery Electric Vehicle (BEV)', 'Plug-in Hybrid Electric Vehicle (PHEV)'], as
sorted_crosstab
```

Out[78]: <Axes: ylabel='make'>

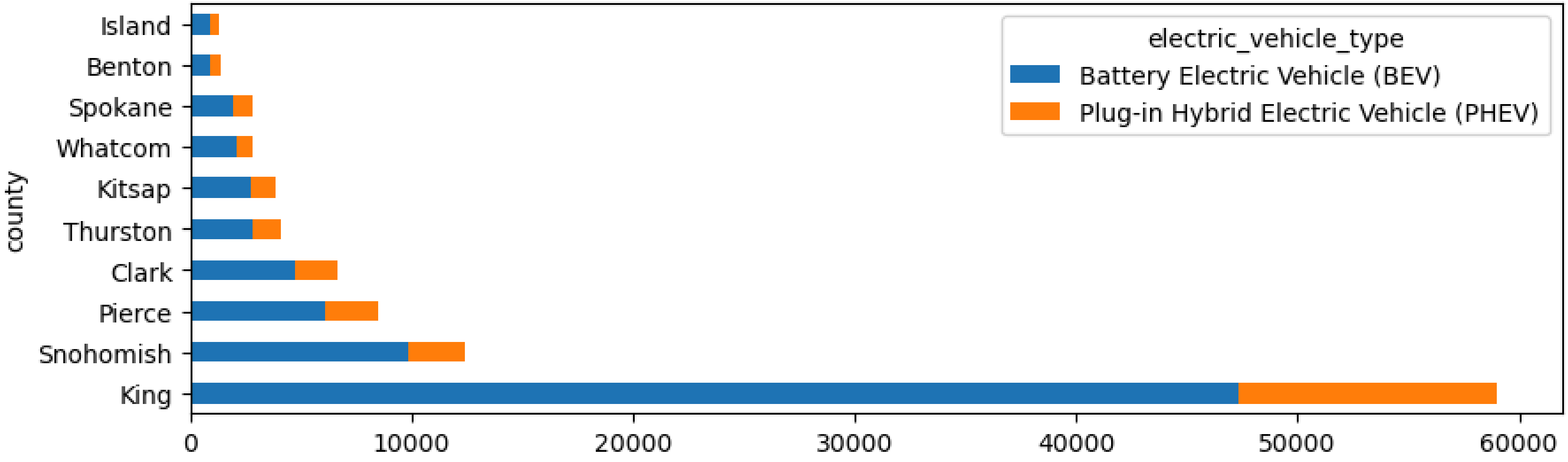


Tesla has more no Hybrid vehicles at all. It is serving it's purpose well.

3. County vs Electric Vehicle Type

In [79]:
```
crosstab = pd.crosstab(data['county'], data['electric_vehicle_type'])
crosstab.sort_values(by=crosstab.columns.tolist(), ascending=False).head(10).plot(kind='barh', figsize=(10,3), stacked=True)
```

Out[79]: <Axes: ylabel='county'>

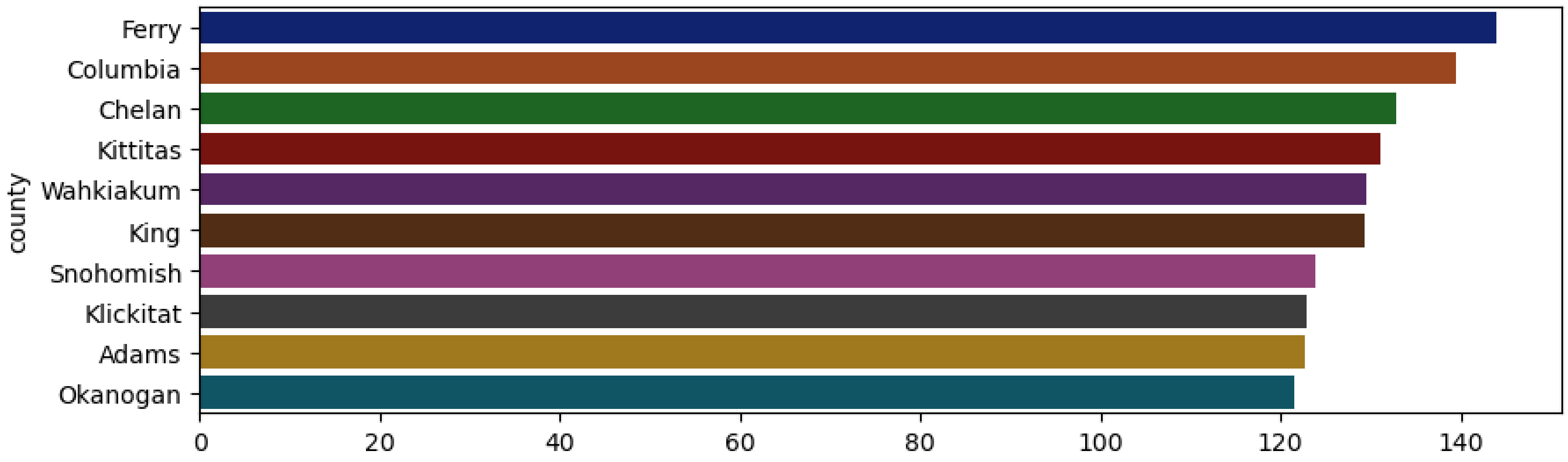


4. Average Electric Range for top 10 counties

In [81]:
```
top10_counties_avg_er = data.groupby('county')['electric_range'].mean().sort_values(ascending=False).head(10)
top10_counties_avg_er
```

Out[81]:
```
county
Ferry         144.037037
Columbia      139.538462
Chelan        132.944954
Kittitas      131.028061
Wahkiakum     129.461538
King          129.369549
Snohomish     123.978327
Klickitat     122.942857
Adams         122.676471
Okanogan      121.536913
Name: electric_range, dtype: float64
```

In [82]:
```
plt.figure(figsize=(10,3))
sns.barplot(x=top10_counties_avg_er.values, y=top10_counties_avg_er.index, palette='dark')
plt.show()
```



Task 2: Create a Choropleth using plotly.express to display the number of EV vehicles based on location

In [83]:
```
data = data.rename(columns={'latitude' : 'longitude',
                     'longitude' : 'latitude'})
```

In [84]:
```
import plotly.express as px
```

In [85]:
```
data['ev_count'] = data.groupby(['state','postal_code','county','latitude', 'longitude'])['postal_code'].transform('count')
```

In [86]:
```
location_data_df = data.groupby(['state', 'postal_code', 'county', 'latitude', 'longitude']).size().reset_index(name='ev_count')
location_data_df
```

Out[86]:

	state	postal_code	county	latitude	longitude	ev_count
0	WA	98001	King	47.3074	-122.23035	465
1	WA	98002	King	47.28317	-122.21698	165
2	WA	98003	King	47.30151	-122.3303	312
3	WA	98004	King	47.61001	-122.1872	2001
4	WA	98005	King	47.64441	-122.1621	829
...	...	...	...	...	...	...
551	WA	99360	Walla Walla	46.04238	-118.66919	4
552	WA	99361	Walla Walla	46.27013	-118.15448	8
553	WA	99362	Walla Walla	46.07068	-118.34261	248
554	WA	99402	Asotin	46.34056	-117.04784	9
555	WA	99403	Asotin	46.41402	-117.04556	39

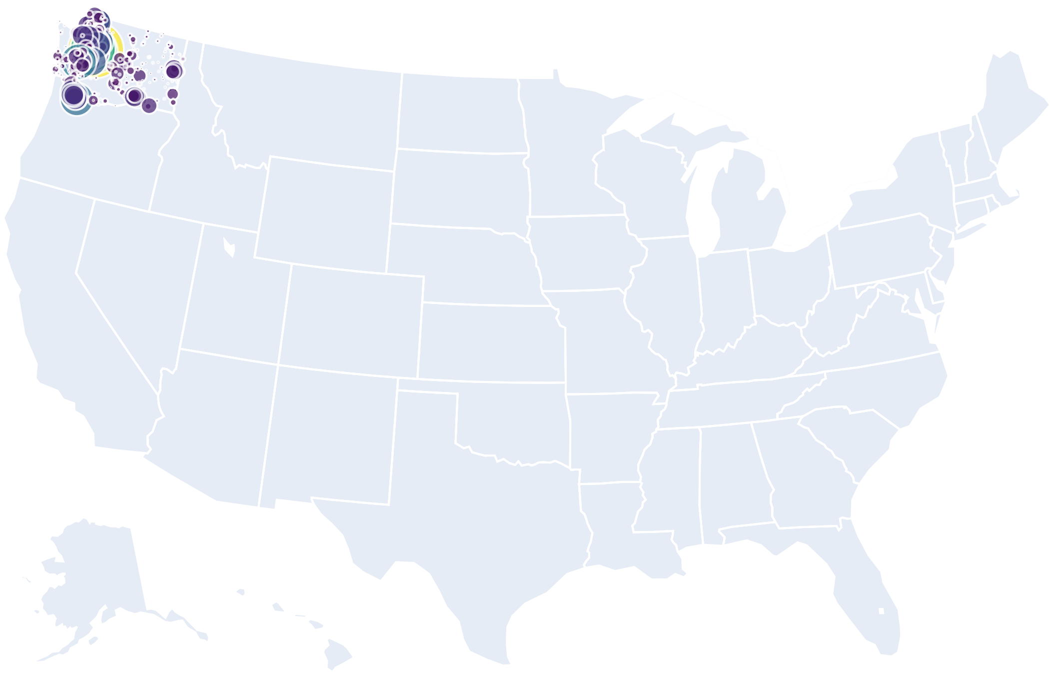
556 rows × 6 columns

In [87]:
```
import plotly.express as px
```

In [88]:
```
fig = px.scatter_geo(location_data_df,
                     lat='latitude',
                     lon='longitude',
                     color='ev_count',
                     hover_name='county',
                     hover_data=['postal_code', 'ev_count'],
                     size='ev_count',
                     title="Number of Electric Vehicles by Location",
```

```
                     color_continuous_scale='Viridis',
                     scope='usa')

fig.show()
```

Number of Electric Vehicles by Location



```
In [ ]:
```