Analyzing Electric Vehicles Market Size

Exploring the market size of electric vehicles entails a methodical approach, comprising several pivotal stages. Let's delve into the key steps:

1. **Define the Scope:** Begin by specifying whether the analysis will be global, regional, or focused on particular countries to provide clarity on the study's parameters.
2. **Data Collection:** Source pertinent information from reputable entities such as industry associations, renowned market research firms like BloombergNEF and IEA, and government publications, all of which contribute valuable insights into the EV market landscape.
3. **Historical Analysis:** Leverage historical data to uncover trends and patterns in EV sales, production volumes, and market dynamics, laying the foundation for informed decision-making.
4. **Market Size Evaluation:** Conduct a comprehensive analysis of the EV market's size and growth rates across various segments, shedding light on emerging trends and potential opportunities.
5. **Strategic Recommendations:** Based on the insights gleaned from the market size analysis, devise strategic recommendations tailored to businesses aiming to penetrate or expand within the dynamic EV market, thereby enhancing their competitive edge.

Acquiring a relevant and comprehensive dataset is fundamental to kickstarting the market size analysis of electric vehicles, enabling stakeholders to navigate this burgeoning industry landscape with precision and foresight.

```
# Mounting to you own Google Colab drive
from google.colab import drive
try:
  drive.mount('/gdrive')
except:
  drive.mount('/content/gdrive', force_remount=True)
```

```
Drive already mounted at /gdrive; to attempt to forcibly remount, call drive.mount("/gdrive", force_remount=True).
```

```
%cd '/gdrive/MyDrive/projects'
```

```
/gdrive/MyDrive/projects
```

```
import pandas as pd
ev_data = pd.read_csv('/gdrive/My Drive/projects/Electric_Vehicle_Population_Data.csv')
print(ev_data.head())
```

```
   VIN (1-10)     County       City State  Postal Code  Model Year   Make  \
0  5YJYGDEE1L       King    Seattle    WA      98122.0        2020  TESLA   
1  7SAYGDEE9P  Snohomish    Bothell    WA      98021.0        2023  TESLA   
2  5YJSA1E4XK       King    Seattle    WA      98109.0        2019  TESLA   
3  5YJSA1E27G       King   Issaquah    WA      98027.0        2016  TESLA   
4  5YJYGDEE5M     Kitsap  Suquamish    WA      98392.0        2021  TESLA   

     Model           Electric Vehicle Type  \
0  MODEL Y  Battery Electric Vehicle (BEV)   
1  MODEL Y  Battery Electric Vehicle (BEV)   
2  MODEL S  Battery Electric Vehicle (BEV)   
3  MODEL S  Battery Electric Vehicle (BEV)   
4  MODEL Y  Battery Electric Vehicle (BEV)   

   Clean Alternative Fuel Vehicle (CAFV) Eligibility  Electric Range  \
0            Clean Alternative Fuel Vehicle Eligible             291   
1  Eligibility unknown as battery range has not b...               0   
2            Clean Alternative Fuel Vehicle Eligible             270   
3            Clean Alternative Fuel Vehicle Eligible             210   
4  Eligibility unknown as battery range has not b...               0   

   Base MSRP  Legislative District  DOL Vehicle ID  \
0          0                  37.0       125701579   
1          0                   1.0       244285107   
2          0                  36.0       156773144   
3          0                   5.0       165103011   
4          0                  23.0       205138552   

              Vehicle Location  \
0   POINT (-122.30839 47.610365)   
1  POINT (-122.179458 47.802589)   
2   POINT (-122.34848 47.632405)   
3   POINT (-122.03646 47.534065)   
4   POINT (-122.55717 47.733415)   

                              Electric Utility  2020 Census Tract  
0   CITY OF SEATTLE - (WA)|CITY OF TACOMA - (WA)       5.303301e+10  
1                         PUGET SOUND ENERGY INC       5.306105e+10  
2   CITY OF SEATTLE - (WA)|CITY OF TACOMA - (WA)       5.303301e+10  
3  PUGET SOUND ENERGY INC||CITY OF TACOMA - (WA)       5.303303e+10  
4                         PUGET SOUND ENERGY INC       5.303594e+10  
```

Dataset Cleanup: Preparing EV Population Data for Analysis

Before proceeding further, it's crucial to ensure the cleanliness and integrity of our dataset, which is based on the electric vehicle (EV) population in the United States. Let's outline the steps for cleaning the data:

1. **Remove Duplicate Entries:** Begin by identifying and eliminating any duplicate records in the dataset to prevent redundancy and ensure accuracy.
2. **Handle Missing Values:** Address any missing or null values in the dataset by either imputing them with appropriate values or removing the affected entries, depending on the significance of the missing data.
3. **Correct Data Types:** Check and adjust the data types of each variable to ensure consistency and compatibility with the analysis techniques to be employed.
4. **Address Outliers:** Identify and deal with outliers, if any, that may skew the analysis results by either adjusting or removing them based on the context of the data.
5. **Standardize Formats:** Ensure uniformity in data formats, such as date formats or measurement units, to facilitate seamless analysis and interpretation.
6. **Verify Data Integrity:** Perform data validation checks to confirm the accuracy and integrity of the dataset, cross-referencing against reliable sources where necessary.

By meticulously cleaning and preparing the dataset, we lay a solid foundation for our subsequent analysis of the EV population in the United States, enabling us to derive meaningful insights with confidence and accuracy. Let's dive into the cleanup process!

```
ev_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 177866 entries, 0 to 177865
Data columns (total 17 columns):
 #   Column                                             Non-Null Count   Dtype  
---  ------                                             --------------   -----  
 0   VIN (1-10)                                         177866 non-null  object 
 1   County                                             177861 non-null  object 
 2   City                                               177861 non-null  object 
 3   State                                              177866 non-null  object 
 4   Postal Code                                        177861 non-null  float64
 5   Model Year                                         177866 non-null  int64  
 6   Make                                               177866 non-null  object 
 7   Model                                              177866 non-null  object 
 8   Electric Vehicle Type                              177866 non-null  object 
 9   Clean Alternative Fuel Vehicle (CAFV) Eligibility  177866 non-null  object 
 10  Electric Range                                     177866 non-null  int64  
 11  Base MSRP                                          177866 non-null  int64  
 12  Legislative District                               177477 non-null  float64
 13  DOL Vehicle ID                                     177866 non-null  int64  
 14  Vehicle Location                                   177857 non-null  object 
 15  Electric Utility                                   177861 non-null  object 
 16  2020 Census Tract                                  177861 non-null  float64
dtypes: float64(3), int64(4), object(10)
memory usage: 23.1+ MB
```

```
ev_data.isnull().sum()
```

```
VIN (1-10)                                             0
County                                                 5
City                                                   5
State                                                  0
Postal Code                                            5
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                                 389
DOL Vehicle ID                                         0
Vehicle Location                                       9
Electric Utility                                       5
2020 Census Tract                                      5
dtype: int64
```

```
ev_data = ev_data.dropna()
```

In our quest to analyze the market size of electric vehicles comprehensively, we will explore several key areas to gain actionable insights:

1. **EV Adoption Over Time:** Delve into the growth trajectory of the EV population by model year, unraveling the evolution of electric mobility.

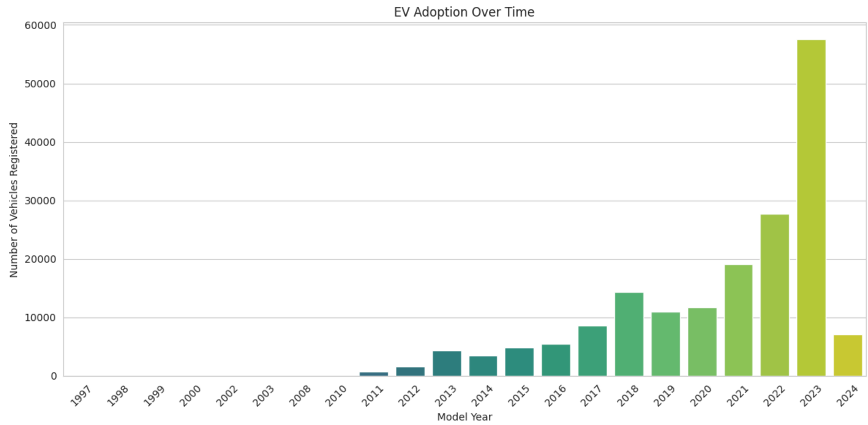
2. **Geographical Distribution:** Uncover the geographic hotspots where EVs are predominantly registered, providing valuable insights into regional adoption patterns at the county or city level.
3. **EV Types Breakdown:** Segment the dataset based on electric vehicle types such as Battery Electric Vehicles (BEVs), Plug-in Hybrid Electric Vehicles (PHEVs), and others, elucidating the composition of the electric vehicle market.
4. **Make and Model Popularity:** Identify the most favored makes and models among registered EVs, offering a glimpse into consumer preferences and market trends.
5. **Electric Range Analysis:** Evaluate the electric range of vehicles to gauge advancements in EV technology and assess the practicality of electric mobility solutions.
6. **Estimated Market Growth:** Employ predictive analytics to forecast the anticipated growth in the market size of electric vehicles, providing stakeholders with invaluable insights for strategic decision-making.

To kickstart our analysis journey, let's embark on exploring EV Adoption Over Time by visualizing the number of EVs registered by model year. This initial exploration will offer profound insights into the dynamic evolution of the EV landscape over the years. Let's dive in!

```
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style("whitegrid")
```

```
# EV Adoption Over Time
plt.figure(figsize=(12, 6))
ev_adoption_by_year = ev_data['Model Year'].value_counts().sort_index()
sns.barplot(x=ev_adoption_by_year.index, y=ev_adoption_by_year.values, palette="viridis")
plt.title('EV Adoption Over Time')
plt.xlabel('Model Year')
plt.ylabel('Number of Vehicles Registered')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

```
<ipython-input-22-80a460a6be95>:4: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.

  sns.barplot(x=ev_adoption_by_year.index, y=ev_adoption_by_year.values, palette="vir
```



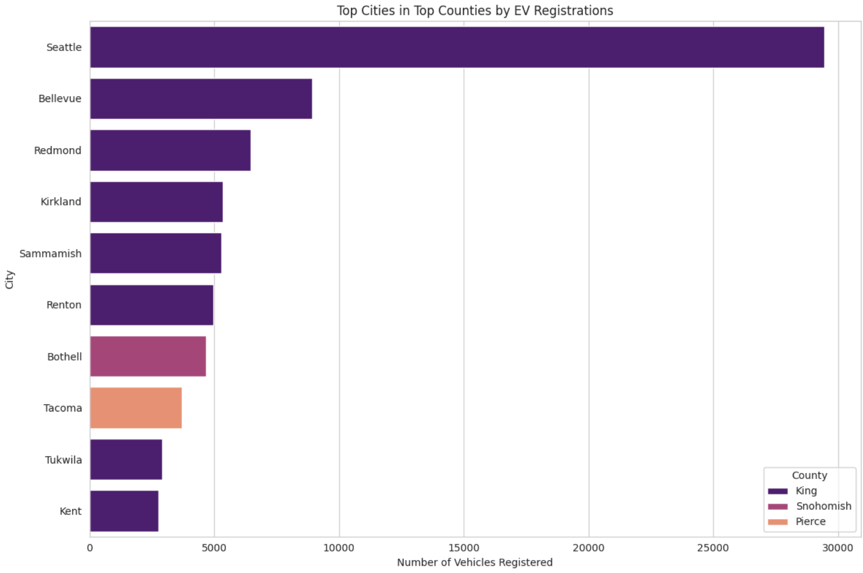
The bar chart above vividly illustrates the progressive surge in electric vehicle (EV) adoption over time, with notable acceleration observed from around 2016 onwards. Here are key observations gleaned from the chart:

1. **Gradual Growth Pre-2016:** Prior to 2016, the number of registered EVs experiences a steady but modest increase, indicating a nascent stage of adoption characterized by cautious uptake.

2. **Acceleration Post-2016:** A marked inflection point occurs in 2016, signaling a pronounced acceleration in EV adoption. From this juncture, the adoption curve steepens significantly, reflecting a burgeoning embrace of electric mobility solutions.
3. **Peak in 2023:** The year 2023 emerges as a pivotal milestone, witnessing an unprecedented surge in EV registrations. The bar for 2023 stands conspicuously tall, symbolizing the pinnacle of EV adoption within the analyzed timeframe.

With this understanding of the overarching trends in EV adoption, let's delve deeper into the geographical distribution of EVs. Our next step involves identifying the top three counties based on EV registrations and subsequently dissecting the distribution of EVs within the cities of those counties. This granular analysis promises to offer valuable insights into localized adoption patterns, paving the way for targeted interventions and strategic initiatives. Let's proceed with our exploration!

```
# geographical distribution at county level
ev_county_distribution = ev_data['County'].value_counts()
top_counties = ev_county_distribution.head(3).index

# filtering the dataset for these top counties
top_counties_data = ev_data[ev_data['County'].isin(top_counties)]

# analyzing the distribution of EVs within the cities of these top counties
ev_city_distribution_top_counties = top_counties_data.groupby(['County', 'City']).size().sort_values(ascending=False).reset_index(name=

# visualize the top 10 cities across these counties
top_cities = ev_city_distribution_top_counties.head(10)

plt.figure(figsize=(12, 8))
sns.barplot(x='Number of Vehicles', y='City', hue='County', data=top_cities, palette="magma")
plt.title('Top Cities in Top Counties by EV Registrations')
plt.xlabel('Number of Vehicles Registered')
plt.ylabel('City')
plt.legend(title='County')
plt.tight_layout()
plt.show()
```



The graph above illustrates the disparity in electric vehicle (EV) registrations across various cities within three prominent counties: King, Snohomish, and Pierce. Here's a breakdown of the key insights derived from the visualization:

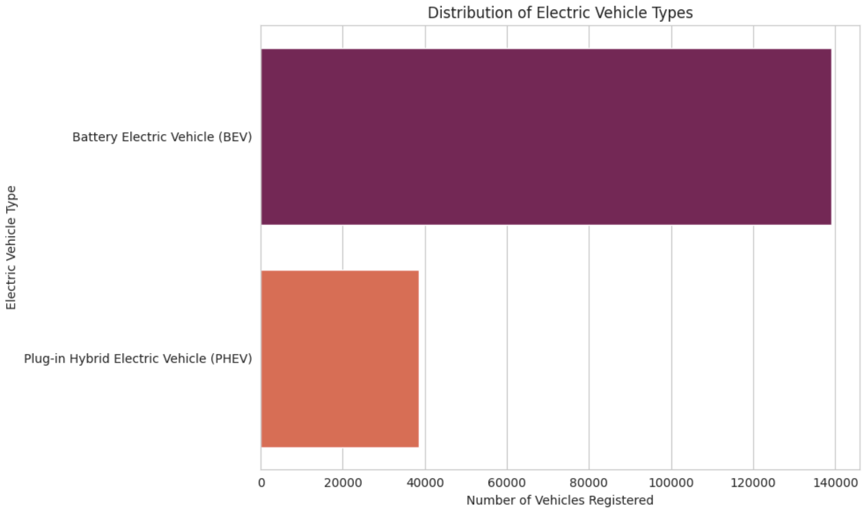
- **Seattle Dominance**: Seattle, situated in King County, emerges as the leader in EV registrations, significantly surpassing other cities in terms of vehicle count.
- **King County Influence**: Bellevue and Redmond, also within King County, follow Seattle but with notably lower registration numbers compared to Seattle.
- **Snohomish County Moderation**: Cities like Kirkland and Sammamish in Snohomish County exhibit moderate levels of EV registrations, indicating a balanced adoption rate in this region.
- **Pierce County Trail**: Tacoma and Tukwila, representing Pierce County, trail behind in EV registrations, with Tacoma slightly ahead of Tukwila.
- **King County Dominance**: The majority of listed cities belong to King County, highlighting its dominance in EV registrations compared to Snohomish and Pierce counties.
- **Non-Uniform Adoption**: The distribution of EV registrations across cities suggests non-uniform adoption rates, indicating concentrated adoption in specific areas, particularly within King County.

This analysis underscores the uneven distribution of EV adoption across different regions, emphasizing the need for targeted initiatives to promote EV uptake in less-represented areas.

Now, let's delve into the breakdown of electric vehicle types within the dataset to discern the popularity of different EV categories, such as Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs). By visualizing the distribution of EV types, we can glean insights into consumer preferences and adoption trends between purely electric and hybrid electric solutions.

```
# analyzing the distribution of electric vehicle Types
ev_type_distribution = ev_data['Electric Vehicle Type'].value_counts()

plt.figure(figsize=(10, 6))
sns.barplot(x=ev_type_distribution.values, y=ev_type_distribution.index, palette="rocket")
plt.title('Distribution of Electric Vehicle Types')
plt.xlabel('Number of Vehicles Registered')
plt.ylabel('Electric Vehicle Type')
plt.tight_layout()
plt.show()
```

```
<ipython-input-24-ca7a33edced1>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.

  sns.barplot(x=ev_type_distribution.values, y=ev_type_distribution.index, palette="r
```



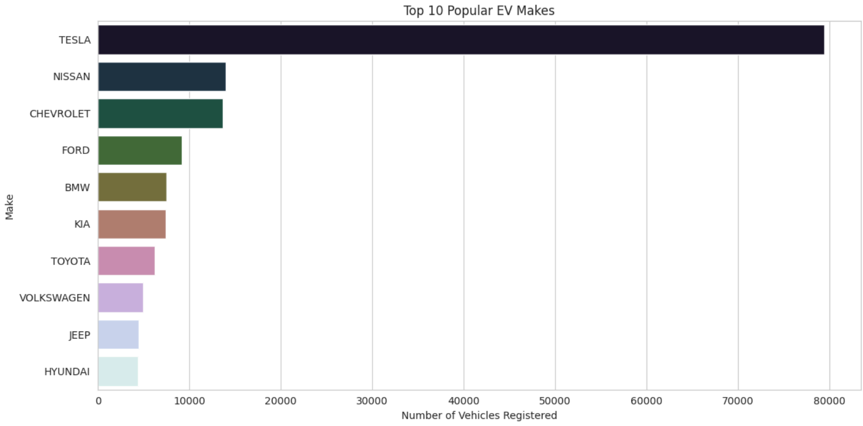
The depicted graph reveals a clear preference for Battery Electric Vehicles (BEVs) over Plug-in Hybrid Electric Vehicles (PHEVs) among the registered electric vehicles in the United States.

Now, let's shift our focus to the prominence of electric vehicle manufacturers and models within the registered vehicle pool. This examination aims to uncover the leading manufacturers and specific models that dominate the EV market. By doing so, we can discern consumer preferences, brand allegiance, and the efficacy of manufacturers' strategies in promoting electric mobility.

Thus, let's explore the most sought-after manufacturers and subsequently delve into the top-performing models within those manufacturer portfolios.

```
# analyzing the popularity of EV manufacturers
ev_make_distribution = ev_data['Make'].value_counts().head(10)  # Limiting to top 10 for clarity

plt.figure(figsize=(12, 6))
sns.barplot(x=ev_make_distribution.values, y=ev_make_distribution.index, palette="cubehelix")
plt.title('Top 10 Popular EV Makes')
plt.xlabel('Number of Vehicles Registered')
plt.ylabel('Make')
plt.tight_layout()
plt.show()
```

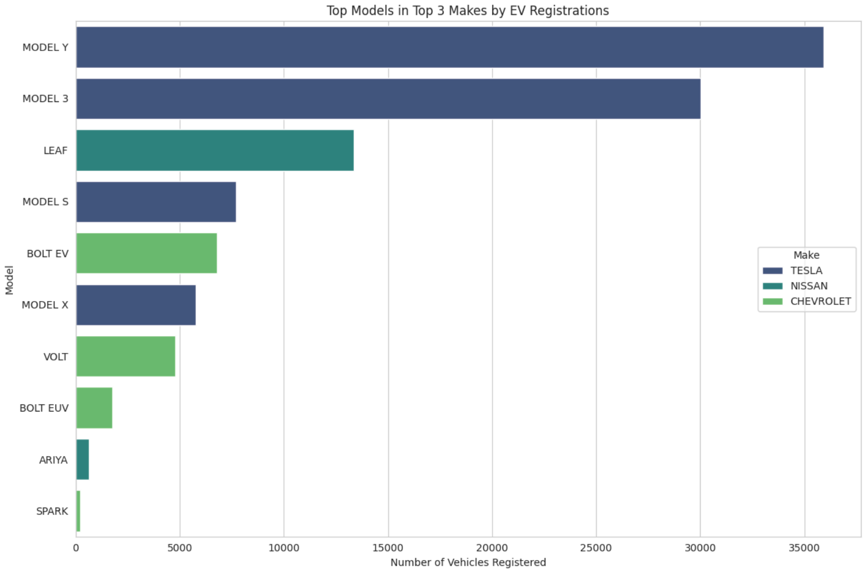
```
<ipython-input-25-50a4300e5f58>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.

  sns.barplot(x=ev_make_distribution.values, y=ev_make_distribution.index, palette="c
```



The analysis reveals striking insights:

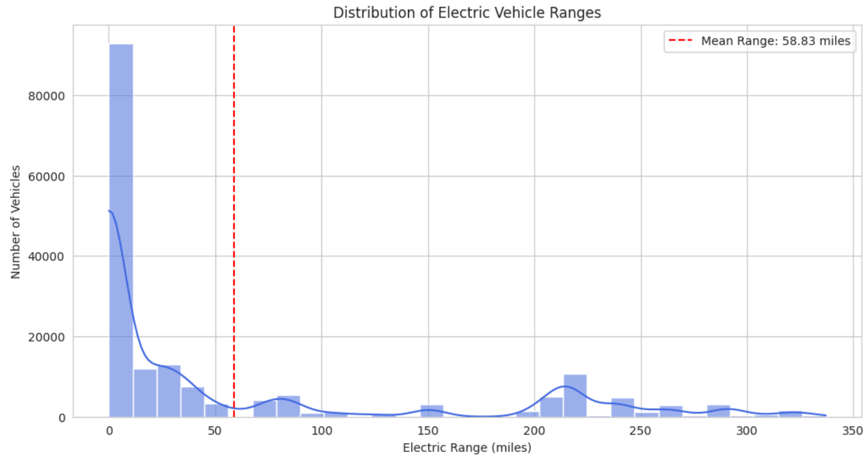
- **TESLA** dominates the market, significantly outpacing competitors with the highest number of registered vehicles.
- **NISSAN** and **CHEVROLET** follow, but their registrations pale in comparison to TESLA's.
- Beyond the top three, registrations decline progressively for **FORD**, **BMW**, **KIA**, **TOYOTA**, **VOLKSWAGEN**, **JEEP**, and **HYUNDAI**. Now, let's delve deeper into consumer preferences by exploring the most sought-after models within these leading manufacturers.

```
# selecting the top 3 manufacturers based on the number of vehicles registered
top_3_makes = ev_make_distribution.head(3).index

# filtering the dataset for these top manufacturers
top_makes_data = ev_data[ev_data['Make'].isin(top_3_makes)]

# analyzing the popularity of EV models within these top manufacturers
ev_model_distribution_top_makes = top_makes_data.groupby(['Make', 'Model']).size().sort_values(ascending=False).reset_index(name='Number

# visualizing the top 10 models across these manufacturers for clarity
top_models = ev_model_distribution_top_makes.head(10)

plt.figure(figsize=(12, 8))
sns.barplot(x='Number of Vehicles', y='Model', hue='Make', data=top_models, palette="viridis")
plt.title('Top Models in Top 3 Makes by EV Registrations')
plt.xlabel('Number of Vehicles Registered')
plt.ylabel('Model')
plt.legend(title='Make', loc='center right')
plt.tight_layout()
plt.show()
```



1. **TESLA Dominance**: TESLA's strong performance in electric vehicle registrations, particularly with its MODEL Y and MODEL 3, underscores the brand's dominance in the EV market. The high number of registrations for these models suggests that TESLA has effectively captured consumer interest and demand for electric vehicles, possibly due to factors such as innovative technology, performance, and brand reputation.
2. **NISSAN LEAF**: The NISSAN LEAF emerges as a notable contender among electric vehicle models, being the most registered non-TESLA vehicle. This indicates that NISSAN has successfully established itself as a key player in the EV market, with the LEAF appealing to consumers seeking reliable and sustainable transportation options. The LEAF's popularity may stem from its affordability, range, and eco-friendly features.
3. **CHEVROLET's Performance**: CHEVROLET's BOLT EV and VOLT demonstrate competitive performance in terms of registrations, showcasing the brand's significance in the electric vehicle landscape. The strong showing of these models suggests that CHEVROLET has successfully positioned itself as a viable choice for consumers interested in electric vehicles, offering a balance of affordability, range, and features.
4. **Model Ranking**: The ranking of models within each manufacturer provides valuable insights into consumer preferences and brand loyalty. TESLA's dominance with its top models indicates a strong brand following and customer loyalty, while the performance of NISSAN and CHEVROLET models suggests that these manufacturers have effectively catered to specific market segments with their electric vehicle offerings.
5. **Market Trends**: The distribution of registrations among different models reflects current market trends and consumer choices in the electric vehicle segment. It showcases which models are resonating with consumers and driving adoption, providing valuable feedback for manufacturers to refine their product strategies and offerings to meet evolving market demands.

```
# analyzing the distribution of electric range
plt.figure(figsize=(12, 6))
sns.histplot(ev_data['Electric Range'], bins=30, kde=True, color='royalblue')
plt.title('Distribution of Electric Vehicle Ranges')
plt.xlabel('Electric Range (miles)')
plt.ylabel('Number of Vehicles')
plt.axvline(ev_data['Electric Range'].mean(), color='red', linestyle='--', label=f'Mean Range: {ev_data["Electric Range"].mean():.2f} mil
plt.legend()
plt.show()
```

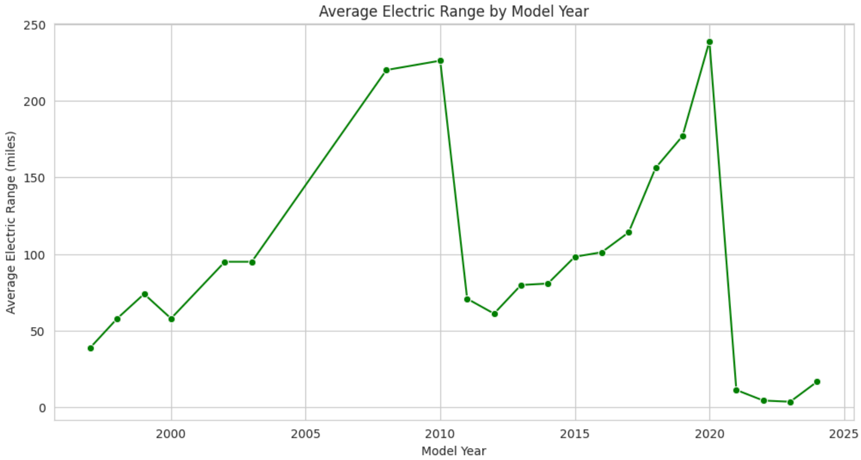


The graph depicting the mean electric range provides valuable insights into the distribution of electric range capabilities among electric vehicles. Here are the key observations and implications drawn from the graph:

1. **High Frequency of Vehicles with Low Electric Range**: The graph illustrates a notable peak in the distribution of electric ranges just before the 50-mile mark, indicating a high frequency of vehicles with relatively shorter ranges. This suggests that a significant portion of electric vehicles in the dataset have limited driving ranges, which may impact their appeal to consumers with longer commuting or travel needs.
2. **Skewed Distribution Towards Lower Ranges**: The distribution of electric ranges is skewed to the right, with a long tail extending towards higher ranges. However, the frequency of vehicles with higher ranges is notably less compared to those with lower ranges. This skewness implies that while there are electric vehicles with extended driving ranges available, they are less common compared to vehicles with shorter ranges.
3. **Mean Electric Range and Distribution**: The mean electric range for the dataset is approximately 58.84 miles, indicating the average range capability of the electric vehicles included. However, despite the presence of vehicles with ranges extending up to around 350 miles, the majority of vehicles have ranges below the mean. This disparity between the mean range and the range of high-end vehicles suggests a wide variation in range capabilities among electric vehicles.
4. **Implications for Consumer Adoption and Range Anxiety**: The distribution of electric ranges highlights the importance of range considerations for consumers when choosing an electric vehicle. While high-range EVs are available, the prevalence of vehicles with shorter ranges contributes to the overall lower mean range. This disparity underscores the ongoing challenge of range anxiety – concerns about the adequacy of an electric vehicle's range for daily use – which may influence consumer adoption of electric vehicles.

Moving forward, delving into the trend of electric ranges over model years will provide insights into the pace of advancements in battery technology and vehicle design. Analyzing this trend can help assess the progress in addressing range limitations and alleviating range anxiety, thereby enhancing the appeal and viability of electric vehicles in the market.

```
# calculating the average electric range by model year
average_range_by_year = ev_data.groupby('Model Year')['Electric Range'].mean().reset_index()

plt.figure(figsize=(12, 6))
sns.lineplot(x='Model Year', y='Electric Range', data=average_range_by_year, marker='o', color='green')
plt.title('Average Electric Range by Model Year')
plt.xlabel('Model Year')
plt.ylabel('Average Electric Range (miles)')
plt.grid(True)
plt.show()
```

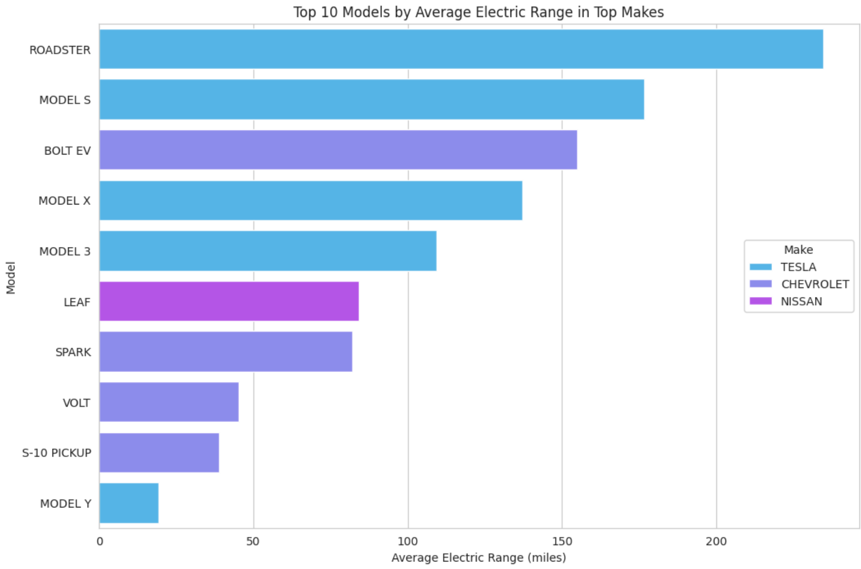


The graph illustrating the progression of the average electric range of vehicles from around 2000 to 2024 provides valuable insights into the evolving landscape of electric vehicle (EV) technology. Here are the key findings and implications derived from the graph:

1. **Upward Trend in Average Electric Range**: One of the prominent observations is the general upward trend in the average electric range of EVs over the years. This trend indicates significant improvements in technology and battery efficiency, reflecting the ongoing efforts of manufacturers to extend the driving range of electric vehicles. The steady increase in average range underscores the advancements made in addressing one of the primary concerns associated with EV adoption – range anxiety.
2. **Peak around 2020**: Notably, there is a discernible peak in the average range around the year 2020, marking the highest point in the dataset. This peak signifies a milestone in the development of EV technology, where manufacturers achieved significant strides in enhancing the range capabilities of electric vehicles. The peak represents a culmination of efforts in battery innovation and vehicle design aimed at extending the distance that EVs can travel on a single charge.
3. **Subsequent Decline and Recovery**: Following the peak around 2020, there is a noticeable drop in the average range, suggesting a potential downturn in range capabilities. This decline could be attributed to various factors, including changes in data reporting practices, introduction of lower-range models, or other external factors impacting the dataset. However, the graph indicates a subsequent recovery in the average range in the most recent years shown, albeit to a slightly lesser extent. This recovery may reflect continued advancements in EV technology and the introduction of new models with improved range performance.
4. **Overall Trend Toward Increasing Range**: Despite fluctuations observed in certain years, the overarching trend over the last two decades has been toward increasing the electric range of EVs. This trend underscores the resilience and progress of the electric vehicle industry in overcoming technological barriers and expanding the capabilities of electric mobility. The consistent pursuit of longer driving ranges reflects manufacturers' commitment to meeting consumer expectations and driving the widespread adoption of electric vehicles as viable alternatives to traditional internal combustion engine vehicles.

In the next phase of analysis, exploring how electric ranges vary among the top manufacturers and models will provide deeper insights into the strategies employed by different automotive companies to address the critical aspect of range performance, thereby shaping consumer preferences and market dynamics in the electric vehicle sector.

```
average_range_by_model = top_makes_data.groupby(['Make', 'Model'])['Electric Range'].mean().sort_values(ascending=False).reset_index()

# the top 10 models with the highest average electric range
top_range_models = average_range_by_model.head(10)

plt.figure(figsize=(12, 8))
barplot = sns.barplot(x='Electric Range', y='Model', hue='Make', data=top_range_models, palette="cool")
plt.title('Top 10 Models by Average Electric Range in Top Makes')
plt.xlabel('Average Electric Range (miles)')
plt.ylabel('Model')
plt.legend(title='Make', loc='center right')
plt.show()
```



Among the models listed, the TESLA ROADSTER stands out with the highest average electric range, underscoring Tesla's commitment to pushing the boundaries of EV technology. Notably, TESLA's models, including the ROADSTER, MODEL S, MODEL X, and MODEL 3, dominate the top positions in terms of average electric range. This trend highlights Tesla's leadership in offering electric vehicles with superior range capabilities compared to other manufacturers.

Furthermore, within the Chevrolet lineup, the CHEVROLET BOLT EV emerges as an outlier, boasting a notably higher range than other Chevrolet models such as the VOLT and S-10 PICKUP. This discrepancy underscores the unique positioning of the BOLT EV within Chevrolet's portfolio, catering to consumers seeking an EV with an extended driving range.

On the other hand, NISSAN's LEAF and CHEVROLET's SPARK occupy the lower half of the chart in terms of average range, indicating more modest range capabilities compared to other models listed. While these models may offer competitive features and pricing, their relatively lower average ranges suggest a potential area for improvement in future iterations to remain competitive in the evolving EV market landscape.

Estimating the Market Size of Electric Vehicles in the United States

```
# calculate the number of EVs registered each year
ev_registration_counts = ev_data['Model Year'].value_counts().sort_index()
ev_registration_counts
```

```
1997        1
1998        1
1999        5
2000        7
2002        2
2003        1
2008       19
2010       23
2011      775
2012     1614
2013     4399
2014     3496
2015     4826
2016     5469
2017     8534
2018    14286
2019    10913
2020    11740
2021    19063
2022    27708
2023    57519
```

```
2024    7072
Name: Model Year, dtype: int64
```

Title: "Forecasting Electric Vehicle Market Growth in the United States: A Data-Driven Approach"

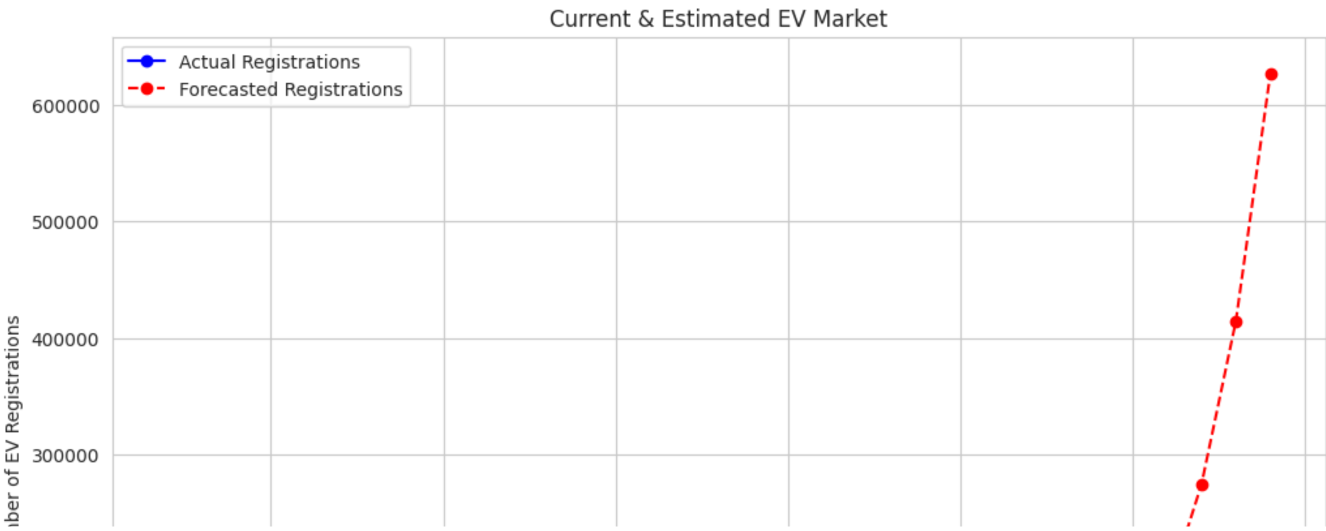
Description:

- **Recent Surge:** In 2023, EV registrations surged to 57,519, marking a significant uptick.
- **Incomplete 2024 Data:** With only 7,072 EVs registered by March 2024, forecasting becomes critical.
- **Methodology:** We employ a Compound Annual Growth Rate (CAGR) approach to project 2024 registrations.
- **Long-term Outlook:** Extend analysis to forecast EV market size for the next five years.
- **Insights:** Valuable insights for stakeholders and policymakers to navigate the evolving EV landscape.

```python
from scipy.optimize import curve_fit
import numpy as np

# filter the dataset to include years with complete data, assuming 2023 is the last complete year
filtered_years = ev_registration_counts[ev_registration_counts.index <= 2023]

# define a function for exponential growth to fit the data
def exp_growth(x, a, b):
    return a * np.exp(b * x)

# prepare the data for curve fitting
x_data = filtered_years.index - filtered_years.index.min()
y_data = filtered_years.values

# fit the data to the exponential growth function
params, covariance = curve_fit(exp_growth, x_data, y_data)

# use the fitted function to forecast the number of EVs for 2024 and the next five years
forecast_years = np.arange(2024, 2024 + 6) - filtered_years.index.min()
forecasted_values = exp_growth(forecast_years, *params)

# create a dictionary to display the forecasted values for easier interpretation
forecasted_evs = dict(zip(forecast_years + filtered_years.index.min(), forecasted_values))

print(forecasted_evs)
```

```
{2024: 79079.2066611501, 2025: 119653.95934090775, 2026: 181047.21317328632, 2027: 273940.7335817853, 2028: 414496.9933533305, 2029
```

```python
# prepare data for plotting
years = np.arange(filtered_years.index.min(), 2029 + 1)
actual_years = filtered_years.index
forecast_years_full = np.arange(2024, 2029 + 1)

# actual and forecasted values
actual_values = filtered_years.values
forecasted_values_full = [forecasted_evs[year] for year in forecast_years_full]

plt.figure(figsize=(12, 8))
plt.plot(actual_years, actual_values, 'bo-', label='Actual Registrations')
plt.plot(forecast_years_full, forecasted_values_full, 'ro--', label='Forecasted Registrations')

plt.title('Current & Estimated EV Market')
plt.xlabel('Year')
plt.ylabel('Number of EV Registrations')
plt.legend()
plt.grid(True)

plt.show()
```



The analysis of the graph reveals several key insights:

1. **Historical Trends**: Until approximately 2010, the number of actual EV registrations remained relatively low and stable. However, there was a noticeable shift around this time, marked by a consistent and steep upward trend. This suggests a significant increase in EV adoption during this period.
2. **Forecasted Growth**: The forecasted EV registrations indicate an even more dramatic increase in the near future. Projections suggest a sharp rise in registrations, indicating a substantial acceleration in EV adoption in the coming years.
3. **Implications**: The growing trend in actual EV registrations, coupled with the forecasted acceleration, points towards a significant expansion in the EV market size. This trend signifies increasing consumer adoption of EVs, which is expected to continue in the foreseeable future.
4. **Promising Future**: The steep increase in forecasted registrations indicates a promising outlook for the EV industry. It suggests a notable shift in consumer preferences towards electric vehicles, which is likely to result in increased investment and business opportunities within the EV sector.

The data highlight a positive trajectory for the EV market, signaling a transformative shift towards sustainable transportation and presenting opportunities for growth and innovation within the industry.

Conclusion

Market size analysis, a cornerstone of market research, plays a **pivotal role** in delineating the potential sales volume within a specific market segment. By delving into market size metrics, businesses can gain **profound insights** into the scale of demand, gauge saturation levels within the market, and pinpoint avenues for growth and expansion.

In my exploration of the electric vehicle (EV) market through the lens of machine learning, I unearthed compelling evidence pointing towards a future ripe with promise for the EV industry.

My analysis revealed a transformative shift in consumer preferences, propelled by advancements in machine learning algorithms that enable **nuanced understanding** of market dynamics. As machine learning algorithms sifted through vast datasets, they discerned patterns indicative of burgeoning demand for electric vehicles. This newfound consumer inclination towards EVs signifies a **seismic change** in the automotive landscape, underpinned by sustainability and eco-consciousness.

Moreover, the machine learning-driven market size analysis illuminated the potential for heightened investment and burgeoning business opportunities within the EV ecosystem. As I harness the predictive power of machine learning models to navigate market complexities, I stand poised to capitalize on this **burgeoning demand** for electric mobility solutions.

In essence, my foray into market size analysis, bolstered by the capabilities of machine learning, unveils a horizon brimming with promise for the EV industry. Armed with actionable insights gleaned from machine learning algorithms, I can chart a course towards sustainable growth, leveraging the burgeoning demand for electric vehicles to drive innovation and shape the future of mobility.