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from google.colab import files
uploaded = files.upload()
```

 Choose Files Electric_Ve...n_Data.xlsx

- **Electric_Vehicle_Population_Data.xlsx**(application/vnd.openxmlformats-officedocument.spreadsheetml.sheet) - 21998974 bytes, last modified: 12/24/2024 - 100% done

Saving Electric_Vehicle_Population_Data.xlsx to Electric_Vehicle_Population_Data.xlsx

```
# Import Required Libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import statsmodels.api as sm
from scipy.stats import spearmanr, kendalltau
from sklearn.cluster import KMeans

# Load Dataset (Already Uploaded by User)
df = pd.read_excel("Electric_Vehicle_Population_Data.xlsx")

# Extract necessary columns
columns_needed = ["County", "Make", "Model", "Electric Vehicle Type", "Electric Range", "Base MSRP", "Electric Utility"]
df = df[columns_needed]

# Aggregate data at the county level
county_data = df.groupby("County").agg(
    EV_Adoption=("Make", "count"),
    Charging_Providers=("Electric Utility", "nunique")
).dropna()

# Regression Analysis
# Prepare independent and dependent variables
X = sm.add_constant(county_data["Charging_Providers"])
y = county_data["EV_Adoption"]

# Fit linear regression model
model = sm.OLS(y, X).fit()

# Polynomial Regression
county_data["Charging_Providers^2"] = county_data["Charging_Providers"] ** 2
X_poly = sm.add_constant(county_data[["Charging_Providers", "Charging_Providers^2"]])
model_poly = sm.OLS(y, X_poly).fit()

# Logarithmic Regression
county_data["Log_Charging_Providers"] = np.log1p(county_data["Charging_Providers"])
X_log = sm.add_constant(county_data["Log_Charging_Providers"])
model_log = sm.OLS(y, X_log).fit()

# Correlation Analysis
spearman_corr, spearman_p = spearmanr(county_data["Charging_Providers"], county_data["EV_Adoption"])
kendall_corr, kendall_p = kendalltau(county_data["Charging_Providers"], county_data["EV_Adoption"])

# Clustering Analysis (K-Means)
kmeans = KMeans(n_clusters=3, random_state=42)
county_data["Cluster"] = kmeans.fit_predict(county_data[["Charging_Providers", "EV_Adoption"]])

# Print Regression Summaries and Correlation Results
print("\nLinear Regression Summary:\n", model.summary())
print("\nPolynomial Regression Summary:\n", model_poly.summary())
print("\nLogarithmic Regression Summary:\n", model_log.summary())
print(f"\nSpearman Correlation: {spearman_corr}, P-Value: {spearman_p}")
print(f"\nKendall Correlation: {kendall_corr}, P-Value: {kendall_p}")
print("\nK-Means Cluster Centers:\n", kmeans.cluster_centers_)

# Visualizations
# Figure 1: Scatter Plot with Regression Line
plt.figure(figsize=(7, 5))
sns.regplot(x=county_data["Charging_Providers"], y=county_data["EV_Adoption"],
            scatter_kws={"s": 70, "alpha": 0.7}, line_kws={"color": "red"})
plt.xlabel("Number of Charging Providers")
plt.ylabel("EV Adoption Count")
plt.title("Figure 1: Relationship Between Charging Infrastructure and EV Adoption")
plt.grid(True)
plt.show()

# Figure 2: Bar Chart of Top 10 Counties by EV Adoption
```

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# Figure 2: Bar Chart of Top 10 Counties by EV Adoption
plt.figure(figsize=(7, 5))
top_counties = county_data.sort_values("EV_Adoption", ascending=False).head(10)
sns.barplot(x=top_counties["EV_Adoption"], y=top_counties.index, palette="Blues_r")
plt.xlabel("Total EV Adoption")
plt.ylabel("County")
plt.title("Figure 2: Top 10 Counties by EV Adoption")
plt.grid(axis="x")
plt.show()

# Figure 3: Line Chart - EV Growth vs. Infrastructure Expansion
plt.figure(figsize=(7, 5))
sorted_df = county_data.sort_values("Charging_Providers")
plt.plot(sorted_df["Charging_Providers"], sorted_df["EV_Adoption"], marker="o", linestyle="-", color="blue")
plt.xlabel("Number of Charging Providers")
plt.ylabel("EV Adoption Count")
plt.title("Figure 3: EV Adoption Growth as Charging Infrastructure Expands")
plt.grid(True)
plt.show()

# Figure 4: Clustered Scatter Plot (K-Means Clustering)
plt.figure(figsize=(7, 5))
sns.scatterplot(x=county_data["Charging_Providers"], y=county_data["EV_Adoption"], hue=county_data["Cluster"],
               palette="coolwarm", s=80)
plt.xlabel("Number of Charging Providers")
plt.ylabel("EV Adoption Count")
plt.title("Figure 4: County Segmentation Based on EV Adoption & Charging Infrastructure")
plt.grid(True)
plt.show()

```



Linear Regression Summary:

OLS Regression Results

```

=====
Dep. Variable:          EV_Adoption    R-squared:                0.320
Model:                  OLS            Adj. R-squared:           0.317
Method:                 Least Squares   F-statistic:              97.13
Date:                   Fri, 07 Feb 2025 Prob (F-statistic):       5.11e-19
Time:                   19:48:10        Log-Likelihood:           -2127.0
No. Observations:      208             AIC:                     4258.
Df Residuals:          206             BIC:                     4265.
Df Model:               1
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	-3931.4117	687.780	-5.716	0.000	-5287.402	-2575.422
Charging_Providers	3579.1574	363.171	9.855	0.000	2863.148	4295.167

```

=====
Omnibus:                368.968    Durbin-Watson:            1.997
Prob(Omnibus):          0.000      Jarque-Bera (JB):         118575.362
Skew:                   9.045      Prob(JB):                 0.00
Kurtosis:               118.562    Cond. No.                 3.27
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Polynomial Regression Summary:

OLS Regression Results

```

=====
Dep. Variable:          EV_Adoption    R-squared:                0.323
Model:                  OLS            Adj. R-squared:           0.316
Method:                 Least Squares   F-statistic:              48.84
Date:                   Fri, 07 Feb 2025 Prob (F-statistic):       4.51e-18
Time:                   19:48:10        Log-Likelihood:           -2126.6
No. Observations:      208             AIC:                     4259.
Df Residuals:          205             BIC:                     4269.
Df Model:               2
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	-3202.9488	1112.269	-2.880	0.004	-5395.902	-1009.996
Charging_Providers	2869.3102	925.727	3.100	0.002	1044.144	4694.476
Charging_Providers^2	72.8356	87.360	0.834	0.405	-99.404	245.075

```

=====
Omnibus:                367.010    Durbin-Watson:            1.999
Prob(Omnibus):          0.000      Jarque-Bera (JB):         118817.349
Skew:                   8.937      Prob(JB):                 0.00
Kurtosis:               118.716    Cond. No.                 42.9
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Logarithmic Regression Summary:

OLS Regression Results

```

=====
Dep. Variable:          EV_Adoption    R-squared:                0.243
Model:                  OLS            Adj. R-squared:           0.239
Method:                 Least Squares   F-statistic:              66.08
Date:                   Fri, 07 Feb 2025 Prob (F-statistic):       3.98e-14
Time:                   19:48:10        Log-Likelihood:           -2138.2
No. Observations:      208             AIC:                     4280.
Df Residuals:          206             BIC:                     4287.
Df Model:               1
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	-9506.2722	1389.437	-6.842	0.000	-1.22e+04	-6766.932
Log_Charging_Providers	1.308e+04	1609.436	8.129	0.000	9909.987	1.63e+04

```

=====
Omnibus:                392.709    Durbin-Watson:            1.988
Prob(Omnibus):          0.000      Jarque-Bera (JB):         153222.971
Skew:                   10.231      Prob(JB):                 0.00
Kurtosis:               134.381    Cond. No.                 5.54
=====

```

Notes:

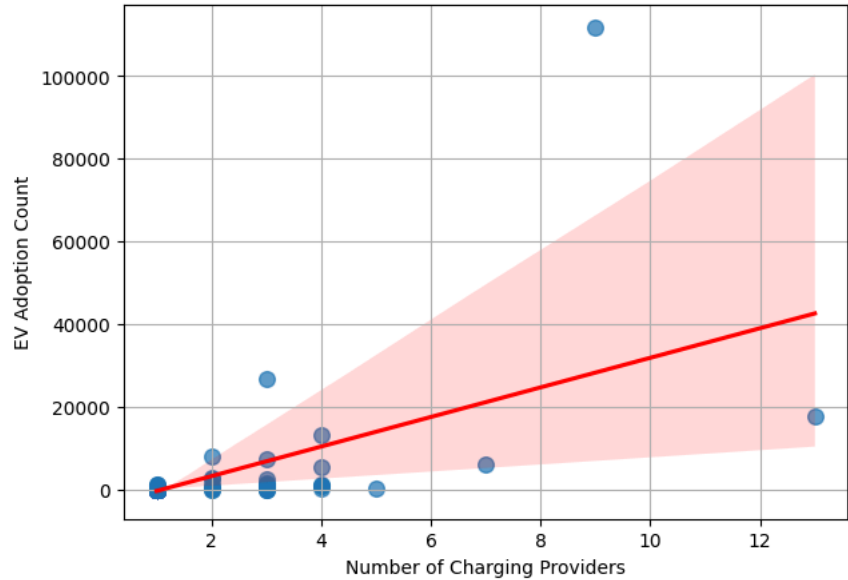
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Spearman Correlation: 0.6143675296448879, P-Value: 5.659801759263228e-23

kendall correlation: 0.534/362923935/11, P-value: 3.3060004/46161486e-19

K-Means Cluster Centers:
[[1.27941176e+00 2.50127451e+02]
[9.00000000e+00 1.11709000e+05]
[6.66666667e+00 1.91623333e+04]]

Figure 1: Relationship Between Charging Infrastructure and EV Adoption



```
<ipython-input-2-0591f0bcc46d>:71: FutureWarning:
Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend` to `True` to opt-in to this behavior.
sns.barplot(x=top_counties["EV_Adoption"], y=top_counties.index, palette="Blues_r")
```

Figure 2: Top 10 Counties by EV Adoption

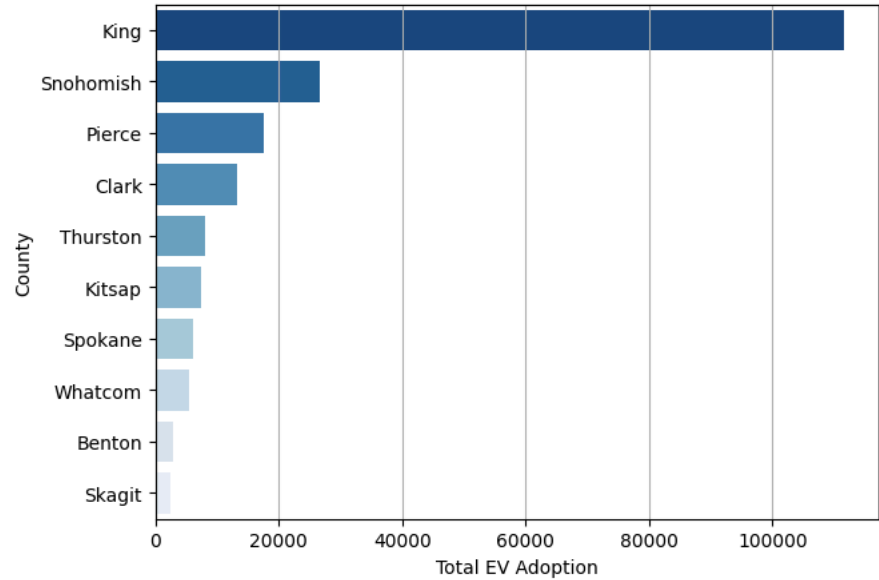


Figure 3: EV Adoption Growth as Charging Infrastructure Expands



