```
import joblib
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.model_selection import RandomizedSearchCV
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

```
df = pd.read_csv("Electric_Vehicle_Population_By_County.csv")
```

```
print("Dataset Shape:", df.shape)
```

```
Dataset Shape: (20819, 10)
```

```
df.head()
```

	Date	County	State	Vehicle Primary Use	Battery Electric Vehicles (BEVs)	Plug-In Hybrid Electric Vehicles (PHEVs)	Electric Vehicle (EV) Total	Non-Electric Vehicle Total	T Vehi
0	September 30 2022	Riverside	CA	Passenger	7	0	7	460	
1	December 31 2022	Prince William	VA	Passenger	1	2	3	188	
2	January 31 2020	Dakota	MN	Passenger	0	1	1	32	
3	June 30 2022	Ferry	WA	Truck	0	0	0	3,575	
4	July 31 2021	Douglas	CO	Passenger	0	1	1	83	

Next steps: Generate code with df | View recommended plots | New interactive sheet

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20819 entries, 0 to 20818
Data columns (total 10 columns):
 #   Column                                     Non-Null Count  Dtype
```

```
 ---  ------                                     --------------  -----
  0   Date                                       20819 non-null  object
  1   County                                     20733 non-null  object
  2   State                                      20733 non-null  object
  3   Vehicle Primary Use                        20819 non-null  object
  4   Battery Electric Vehicles (BEVs)           20819 non-null  object
  5   Plug-In Hybrid Electric Vehicles (PHEVs)   20819 non-null  object
  6   Electric Vehicle (EV) Total                20819 non-null  object
  7   Non-Electric Vehicle Total                 20819 non-null  object
  8   Total Vehicles                             20819 non-null  object
  9   Percent Electric Vehicles                  20819 non-null  float64
dtypes: float64(1), object(9)
memory usage: 1.6+ MB
```

```
df.isnull().sum()
```

	0
Date	0
County	86
State	86
Vehicle Primary Use	0
Battery Electric Vehicles (BEVs)	0
Plug-In Hybrid Electric Vehicles (PHEVs)	0
Electric Vehicle (EV) Total	0
Non-Electric Vehicle Total	0
Total Vehicles	0
Percent Electric Vehicles	0

dtype: int64

```
Q1 = df['Percent Electric Vehicles'].quantile(0.25)
Q3 = df['Percent Electric Vehicles'].quantile(0.75)
IQR = Q3 - Q1

# Define outlier boundaries
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
print('lower_bound:', lower_bound)
print('upper_bound:', upper_bound)

# Identify outliers
outliers = df[(df['Percent Electric Vehicles'] < lower_bound) | (df['Percent Electric Vehic
print("Number of outliers in 'Percent Electric Vehicles':", outliers.shape[0])
```

```
lower_bound: -3.5174999999999996
upper_bound: 6.9025
```

```
Number of outliers in 'Percent Electric Vehicles': 2476
```

```
# Converts the "Date" column to actual datetime objects
df['Date'] = pd.to_datetime(df['Date'], errors='coerce')

# Removes rows where "Date" conversion failed
df = df[df['Date'].notnull()]

# Removes rows where the target (EV Total) is missing
df = df[df['Electric Vehicle (EV) Total'].notnull()]

# Fill missing values
df['County'] = df['County'].fillna('Unknown')
df['State'] = df['State'].fillna('Unknown')

# Confirm remaining nulls
print("Missing after fill:")
print(df[['County', 'State']].isnull().sum())

df.head()
```

```
Missing after fill:
County    0
State     0
dtype: int64
```

	Date	County	State	Vehicle Primary Use	Battery Electric Vehicles (BEVs)	Plug-In Hybrid Electric Vehicles (PHEVs)	Electric Vehicle (EV) Total	Non-Electric Vehicle Total	Total Vehicles
0	2022-09-30	Riverside	CA	Passenger	7	0	7	460	467
1	2022-12-31	Prince William	VA	Passenger	1	2	3	188	191
2	2020-01-31	Dakota	MN	Passenger	0	1	1	32	33
3	2022-06-30	Ferry	WA	Truck	0	0	0	3,575	3,575
4	2021-07-31	Douglas	CO	Passenger	0	1	1	83	84

Next steps: Generate code with df | View recommended plots | New interactive sheet

```
# Cap the outliers - it keeps all the data while reducing the skew from extreme values.

df['Percent Electric Vehicles'] = np.where(df['Percent Electric Vehicles'] > upper_bound, u
                                  np.where(df['Percent Electric Vehicles'] < lower_bound, lo

# Identify outliers
```

```
outliers = df[(df['Percent Electric Vehicles'] < lower_bound) | (df['Percent Electric Vehic
print("Number of outliers in 'Percent Electric Vehicles':", outliers.shape[0])
```

```
Number of outliers in 'Percent Electric Vehicles': 0
```

```
cols_to_convert = [
    'Battery Electric Vehicles (BEVs)',
    'Plug-In Hybrid Electric Vehicles (PHEVs)',
    'Electric Vehicle (EV) Total',
    'Non-Electric Vehicle Total',
    'Total Vehicles',
    'Percent Electric Vehicles'
]

for col in cols_to_convert:
    df[col] = pd.to_numeric(df[col], errors='coerce')

df[cols_to_convert].describe()
```

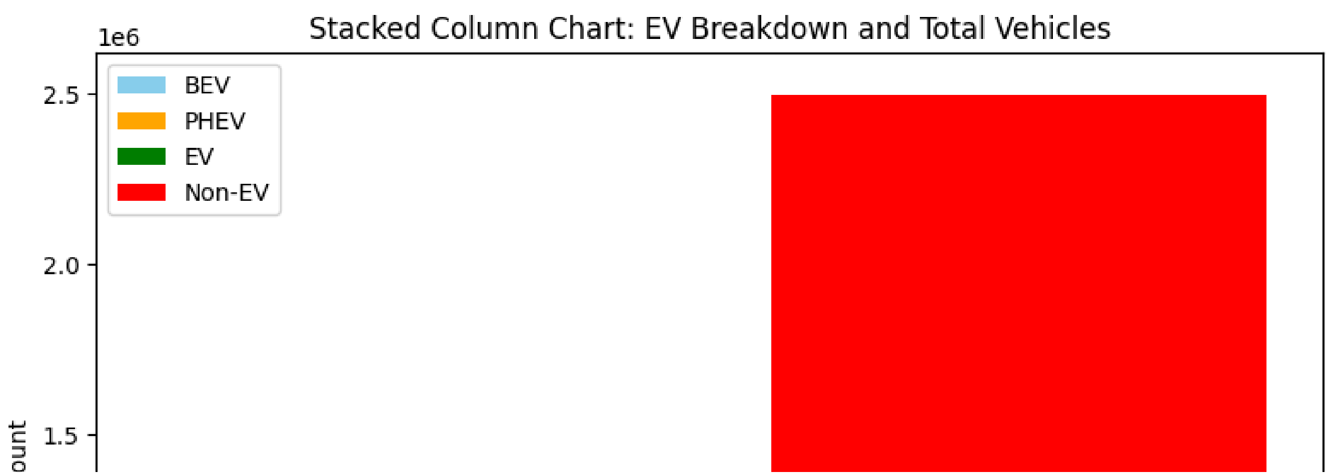
	Battery Electric Vehicles (BEVs)	Plug-In Hybrid Electric Vehicles (PHEVs)	Electric Vehicle (EV) Total	Non-Electric Vehicle Total	Total Vehicles	Percent Electric Vehicles
count	20266.000000	20468.000000	20119.000000	13983.000000	13979.000000	20819.000000
mean	25.855176	21.790942	31.623093	132.845312	134.463767	2.122378
std	102.004224	92.309729	115.742017	174.033916	174.448753	2.277542
min	0.000000	0.000000	0.000000	0.000000	1.000000	0.000000
25%	0.000000	0.000000	1.000000	26.000000	27.000000	0.390000
50%	1.000000	1.000000	1.000000	69.000000	70.000000	1.220000
75%	2.000000	1.000000	3.000000	167.000000	169.000000	2.995000
max	999.000000	999.000000	999.000000	999.000000	998.000000	6.902500

```
ty
groupby('County')['Electric Vehicle (EV) Total'].sum().sort_values(ascending=False).head(3)
df.groupby('County')['Electric Vehicle (EV) Total'].sum().sort_values().head(3)

ies:\n", top_counties)
Counties:\n", bottom_counties)
```

```
Top 3 Counties:
 County
Clallam      39839.0
Jefferson    39683.0
San Juan     39309.0
Name: Electric Vehicle (EV) Total, dtype: float64
```

```
Bottom 3 Counties:
 County
Brown         1.0
Union         1.0
Hood River    1.0
Name: Electric Vehicle (EV) Total, dtype: float64
```

```
# Total sums for stacked column chart
bev_total = df['Battery Electric Vehicles (BEVs)'].sum()
phev_total = df['Plug-In Hybrid Electric Vehicles (PHEVs)'].sum()
ev_total = df['Electric Vehicle (EV) Total'].sum()
non_ev_total = df['Non-Electric Vehicle Total'].sum()
all_total = df['Total Vehicles'].sum()

# Stacked column chart
fig, ax = plt.subplots(figsize=(8, 6))

# Stack EV types
ax.bar('EV Type Breakdown', bev_total, label='BEV', color='skyblue')
ax.bar('EV Type Breakdown', phev_total, bottom=bev_total, label='PHEV', color='orange')

# Stack Total Vehicle categories
ax.bar('All Vehicles', ev_total, label='EV', color='green')
ax.bar('All Vehicles', non_ev_total, bottom=ev_total, label='Non-EV', color='red')

# Final touches
ax.set_ylabel('Vehicle Count')
ax.set_title('Stacked Column Chart: EV Breakdown and Total Vehicles')
ax.legend()
plt.tight_layout()
plt.show()
```




```
# Extract year, month, and date
df['year'] = df['Date'].dt.year
df['month'] = df['Date'].dt.month
df['numeric_date'] = df['Date'].dt.year * 12 + df['Date'].dt.month  # For trend


# Encode County
le = LabelEncoder()
df['county_encoded'] = le.fit_transform(df['County'])
```

```
# Sort for lag creation
df = df.sort_values(['County', 'Date'])


# Assign time index per county
df['months_since_start'] = df.groupby('County').cumcount()

#Lags are only based on past data from the same county
# === Create lag features (1–3 months) ===
for lag in [1, 2, 3]:
    df[f'ev_total_lag{lag}'] = df.groupby('County')['Electric Vehicle (EV) Total'].shift(la

# === Rolling average (3-month, prior) ===
df['ev_total_roll_mean_3'] = df.groupby('County')['Electric Vehicle (EV) Total'] \
                               .transform(lambda x: x.shift(1).rolling(3).mean())

# === Percent change (no fill method) ===
df['ev_total_pct_change_1'] = df.groupby('County')['Electric Vehicle (EV) Total'] \
                                .pct_change(periods=1, fill_method=None)

df['ev_total_pct_change_3'] = df.groupby('County')['Electric Vehicle (EV) Total'] \
                                .pct_change(periods=3, fill_method=None)

# === Clean up any infs/NaNs ===
df['ev_total_pct_change_1'] = df['ev_total_pct_change_1'].replace([np.inf, -np.inf], np.nan
df['ev_total_pct_change_3'] = df['ev_total_pct_change_3'].replace([np.inf, -np.inf], np.nan



# Cumulative EV count per county
df['cumulative_ev'] = df.groupby('County')['Electric Vehicle (EV) Total'].cumsum()

# 6-month rolling linear slope of cumulative growth
df['ev_growth_slope'] = df.groupby('County')['cumulative_ev'].transform(
    lambda x: x.rolling(6).apply(lambda y: np.polyfit(range(len(y)), y, 1)[0] if len(y) ==
)



df = df.dropna().reset_index(drop=True)


df.to_csv('preprocessed_ev_data.csv', index=False)

df.head()
```

	Date	County	State	Vehicle Primary Use	Battery Electric Vehicles (BEVs)	Plug-In Hybrid Electric Vehicles (PHEVs)	Electric Vehicle (EV) Total	Non-Electric Vehicle Total	Total Vehicles
0	2018-05-31	Ada	ID	Passenger	0.0	2.0	2.0	341.0	343.0
1	2018-06-30	Ada	ID	Passenger	0.0	2.0	2.0	332.0	334.0
2	2018-07-31	Ada	ID	Passenger	0.0	2.0	2.0	329.0	331.0
3	2018-08-31	Ada	ID	Passenger	0.0	2.0	2.0	325.0	327.0
4	2018-09-30	Ada	ID	Passenger	0.0	2.0	2.0	327.0	329.0

5 rows × 23 columns

```
features = [
    'months_since_start',
    'county_encoded',
    'ev_total_lag1',
    'ev_total_lag2',
    'ev_total_lag3',
    'ev_total_roll_mean_3',
    'ev_total_pct_change_1',
    'ev_total_pct_change_3',
    'ev_growth_slope',
]

target = 'Electric Vehicle (EV) Total'
X = df[features]
y = df[target]

X.head()
```

	months_since_start	county_encoded	ev_total_lag1	ev_total_lag2	ev_total_lag
0	5	0	2.0	2.0	2.
1	6	0	2.0	2.0	2.
2	7	0	2.0	2.0	2.
3	8	0	2.0	2.0	2.
4	9	0	2.0	2.0	2.

Next steps: Generate code with X | View recommended plots | New interactive sheet

```
X.shape
```

```
(12573, 9)
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, shuffle=False, test_size=0.1)
```

```
y_test.head()
```

	Electric Vehicle (EV) Total
11315	1.0
11316	1.0
11317	1.0
11318	1.0
11319	1.0

dtype: float64

```
# Define param distribution
param_dist = {
    'n_estimators': [100, 150, 200, 250],
    'max_depth': [None, 5, 10, 15],
    'min_samples_split': [2, 4, 6, 8],
    'min_samples_leaf': [1, 2, 3],
    'max_features': ['sqrt', 'log2', None]
}

# Base model
rf = RandomForestRegressor(random_state=42)

# Randomized Search
random_search = RandomizedSearchCV(
    estimator=rf,
    param_distributions=param_dist,
    n_iter=30,  # 30 random combos
    scoring='r2',
    cv=3,
    n_jobs=-1,
    verbose=1,
    random_state=42
)

# Fit model
random_search.fit(X_train, y_train)

# Best model
```

```
model = random_search.best_estimator_
print("Best Parameters:", random_search.best_params_)
```

```
Fitting 3 folds for each of 30 candidates, totalling 90 fits
Best Parameters: {'n_estimators': 200, 'min_samples_split': 4, 'min_samples_leaf
```

```
# Predict and evaluate
y_pred = model.predict(X_test)
```

```
X_test.head()
```

	months_since_start	county_encoded	ev_total_lag1	ev_total_lag2	ev_total_
11315	97	270	1.0	1.0	
11316	98	270	1.0	1.0	
11317	5	271	1.0	1.0	
11318	6	271	1.0	1.0	
11319	7	271	1.0	1.0	

Next steps: Generate code with X_test | View recommended plots | New interactive sheet

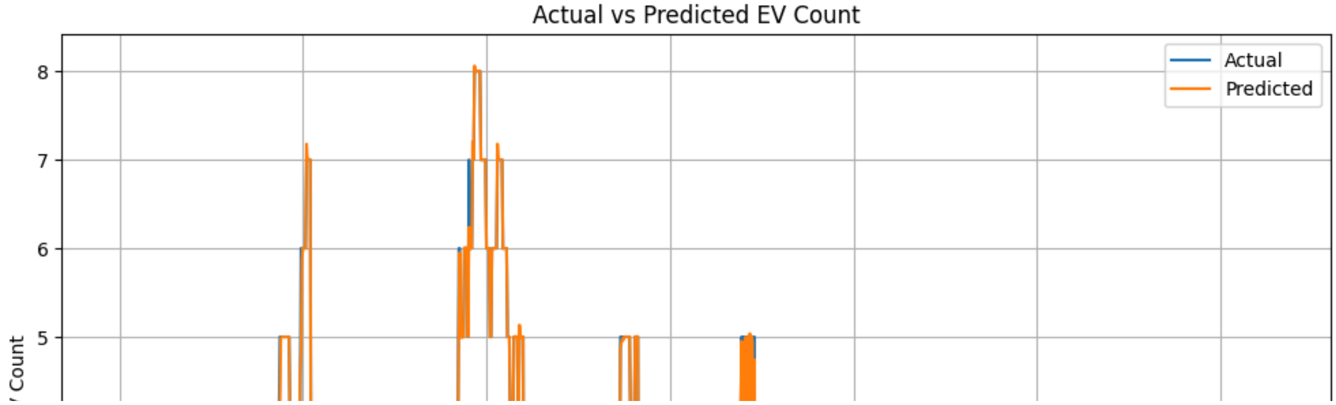
```
# Create a DataFrame with actual and predicted values

comparison_df = pd.DataFrame({
    'Actual EV Count': y_test.values,
    'Predicted EV Count': y_pred
})

# Round for readability
comparison_df['Predicted EV Count'] = comparison_df['Predicted EV Count'].round(2)

# Optionally reset index if needed
comparison_df.reset_index(drop=True, inplace=True)

# Show the first 10 rows
comparison_df.head(10)
```

	Actual EV Count	Predicted EV Count
0	1.0	1.0
1	1.0	1.0
2	1.0	1.0
3	1.0	1.0
4	1.0	1.0
5	1.0	1.0
6	1.0	1.0
7	1.0	1.0
8	1.0	1.0
9	1.0	1.0

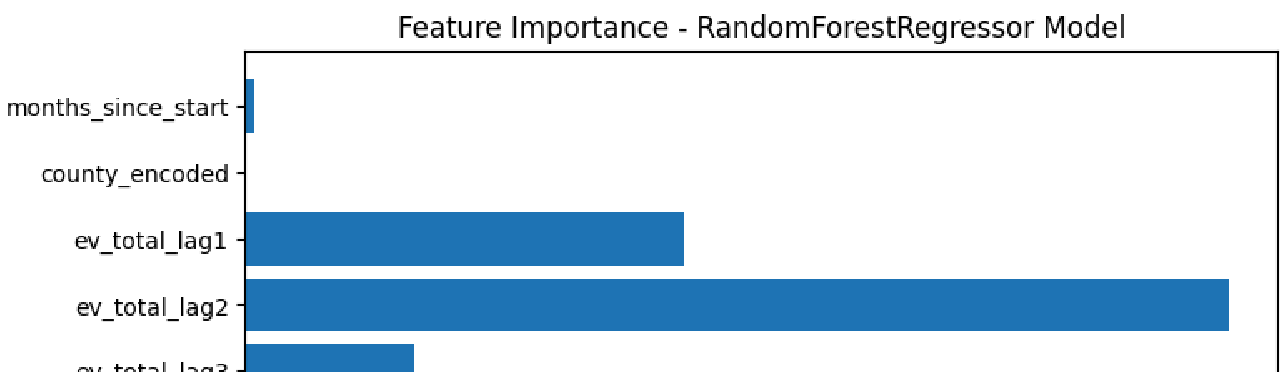
Next steps: Generate code with comparison_df | View recommended plots | New interactive sheet

```
def evaluate(y_true, y_pred):
    mae = mean_absolute_error(y_true, y_pred)
    rmse = np.sqrt(mean_squared_error(y_true, y_pred))
    r2Score = r2_score(y_true, y_pred)
    print(f"MAE: {mae:.2f}, RMSE: {rmse:.2f}, R2 Score: {r2Score:.2f}")

evaluate(y_test, y_pred)

# Plot actual vs predicted
plt.figure(figsize=(10,6))
plt.plot(y_test.values, label='Actual')
plt.plot(y_pred, label='Predicted')
plt.title("Actual vs Predicted EV Count")
plt.xlabel("Sample Index")
plt.ylabel("EV Count")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
MAE: 0.01, RMSE: 0.06, R2 Score: 1.00
```




```
# Corrected the attribute name from get_feature_importance() to feature_importances_
importances = model.feature_importances_

# Plot feature importance
plt.figure(figsize=(8,5))
plt.barh(features, importances)
plt.xlabel('Importance Score')
# Updated the title to reflect that the model is RandomForestRegressor
plt.title('Feature Importance - RandomForestRegressor Model')
plt.gca().invert_yaxis()  # Highest importance on top
plt.show()
```




```
# Define features and target
featuresX = ['County', 'county_encoded']

countyX = df[featuresX]


print("List of unique counties:")
print(df['County'].dropna().unique())

print("Total unique counties:", df['County'].nunique())
```

```
List of unique counties:
['Ada' 'Adams' 'Alameda' 'Albemarle' 'Alexandria' 'Allegheny' 'Allen'
 'Anchorage' 'Anne Arundel' 'Arapahoe' 'Arlington' 'Atlantic' 'Autauga'
 'Baltimore' 'Bartow' 'Beaufort' 'Bell' 'Bergen' 'Berkeley' 'Berkshire'
 'Bexar' 'Boone' 'Boulder' 'Bradley' 'Brevard' 'Broward' 'Bryan' 'Bucks'
 'Burlington' 'Caddo' 'Calvert' 'Camden' 'Canyon' 'Carroll' 'Carson City'
 'Cascade' 'Champaign' 'Charles' 'Charleston' 'Charlottesville'
 'Chesapeake' 'Clackamas' 'Clay' 'Clinton' 'Cobb' 'Cochise' 'Collier'
```

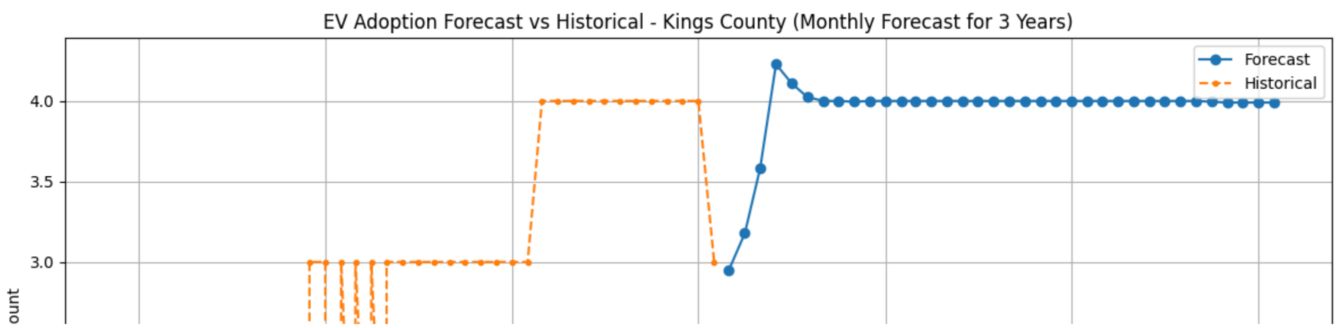
```
 'Collin' 'Columbia' 'Contra Costa' 'Cook' 'Coryell' 'Cumberland'
 'Currituck' 'Dakota' 'Dale' 'Dallas' 'Dane' 'Danville' 'DeKalb' 'Denton'
 'Denver' 'Deschutes' 'District of Columbia' 'Dorchester' 'Douglas'
 'DuPage' 'Duval' 'Eagle' 'Eau Claire' 'El Dorado' 'El Paso' 'Escambia'
 'Essex' 'Fairbanks North Star' 'Fairfax' 'Flathead' 'Fort Bend'
 'Franklin' 'Frederick' 'Fresno' 'Fulton' 'Galveston' 'Garfield' 'Geary'
 'Goochland' 'Greene' 'Guadalupe' 'Gwinnett' 'Hamilton' 'Hampshire'
 'Hardin' 'Harford' 'Harnett' 'Harris' 'Harrison' 'Hawaii' 'Hennepin'
 'Henrico' 'Hillsborough' 'Honolulu' 'Houston' 'Howard' 'Hudson' 'Jackson'
 'James City' 'Jefferson' 'Jones' 'Juneau' 'Kalamazoo' 'Kauai' 'Kent'
 'Kern' 'Kings' 'Klamath' 'Kootenai' 'Lake' 'Lane' 'Laramie' 'Larimer'
 'Las Animas' 'Latah' 'Leavenworth' 'Lee' 'Lewis' 'Lincoln' 'Los Angeles'
 'Loudoun' 'Louisa' 'Lumpkin' 'Madison' 'Manassas' 'Manatee' 'Maricopa'
 'Marin' 'Marion' 'Maui' 'Meade' 'Mecklenburg' 'Mercer' 'Miami-Dade'
 'Middlesex' 'Milwaukee' 'Missoula' 'Mobile' 'Monroe' 'Monterey'
 'Montgomery' 'Moore' 'Morris' 'Multnomah' 'Muscogee' 'Nantucket' 'Napa'
 'Nassau' 'New Haven' 'New London' 'New York' 'Newport' 'Newport News'
 'Norfolk' 'Northampton' 'Nueces' 'Okaloosa' 'Oklahoma' 'Oldham' 'Onslow'
 'Orange' 'Orleans' 'Osceola' 'Otero' 'Owyhee' 'Palm Beach' 'Parker'
 'Pennington' 'Penobscot' 'Philadelphia' 'Pima' 'Pinal' 'Pinellas'
 'Placer' 'Plaquemines' 'Platte' 'Polk' 'Portsmouth' 'Powhatan'
 'Prince George' "Prince George's" 'Prince William' 'Providence' 'Pulaski'
 'Putnam' 'Queens' 'Ramsey' 'Randolph' 'Ray' 'Richland' 'Richmond'
 'Riverside' 'Rock Island' 'Rockdale' 'Rockingham' 'Rogers'
 'RÃ\xado Grande' 'Sacramento' 'Saginaw' 'Salt Lake' 'San Bernardino'
 'San Francisco' 'San Joaquin' 'San Juan' 'San Luis Obispo' 'San Mateo'
 'Sangamon' 'Santa Clara' 'Santa Cruz' 'Santa Fe' 'Santa Rosa' 'Sarasota'
 'Saratoga' 'Sarpy' 'Sedgwick' 'Sevier' 'Shasta' 'Shelby' 'Sheridan'
 'Solano' 'Sonoma' 'Spartanburg' 'St. Clair' 'St. Lawrence' 'St. Louis'
 'St. Lucie' "St. Mary's" 'Stafford' 'Suffolk' 'Sumter' 'Tarrant' 'Texas'
 'Tooele' 'Travis' 'Tulare' 'Tulsa' 'Twin Falls' 'Ulster' 'Unknown' 'Utah'
 'Valencia' 'Ventura' 'Vigo' 'Virginia Beach' 'Volusia' 'Wake'
 'Washington' 'Washoe' 'Washtenaw' 'Wayne' 'Wichita' 'Williams'
 'Williamsburg' 'Williamson' 'Wilson' 'Wood' 'Yamhill' 'Yavapai'
 'Yellowstone' 'Yolo' 'York' 'Yuba']
Total unique counties: 269
```

```
# Set your county name
county = "Kings"

# Encode county
try:
    county_code = le.transform([county])[0]
    print(f"County '{county}' encoded as {county_code}.")
except ValueError:
    print(f"Error: '{county}' not found in LabelEncoder.")
    exit()

# Filter historical data
county_df = df[df['county_encoded'] == county_code].sort_values("numeric_date")
if county_df.empty:
    print(f"Warning: No data found for county '{county}'.")
    exit()

# Prepare EV history
historical_ev = list(county_df['Electric Vehicle (EV) Total'].values[-6:])
cumulative_ev = list(np.cumsum(historical_ev))
```

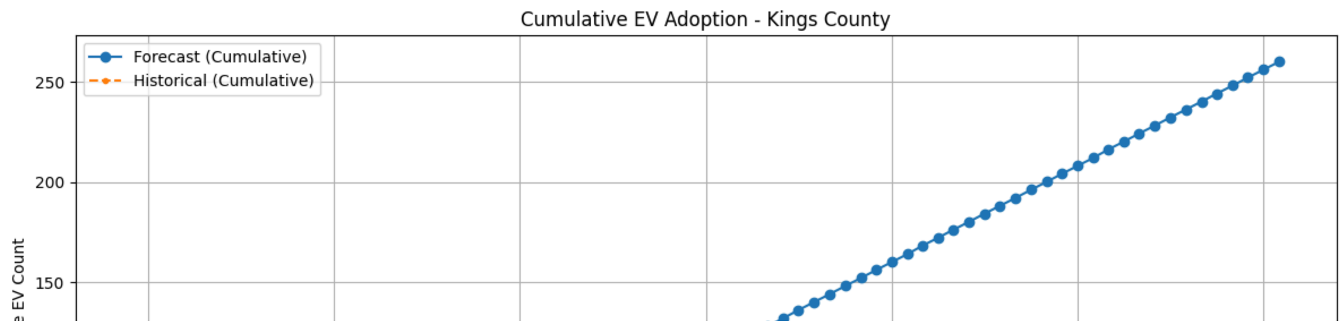
```
slope_history = []
months_since_start = county_df['months_since_start'].max()

historical = county_df[['year', 'month', 'numeric_date', 'Electric Vehicle (EV) Total', 'mo
historical['Source'] = 'Historical'
historical['Date'] = pd.to_datetime(historical[['year', 'month']].assign(day=1))

# Forecast next 36 months
latest_row = county_df.iloc[-1].copy()
future_rows = []

for i in range(1, 37):
    next_date = pd.to_datetime(latest_row['year'] * 100 + latest_row['month'], format='%Y%m
    y, m = next_date.year, next_date.month
    numeric_date = y * 12 + m
    months_since_start += 1

    lag1, lag2, lag3 = historical_ev[-1], historical_ev[-2], historical_ev[-3]
    roll_mean = np.mean([lag1, lag2, lag3])
    pct_change_1 = (lag1 - lag2) / lag2 if lag2 != 0 else 0
    pct_change_3 = (lag1 - lag3) / lag3 if lag3 != 0 else 0

    # Compute slope
    recent_cumulative = cumulative_ev[-6:]
    ev_growth_slope = np.polyfit(range(len(recent_cumulative)), recent_cumulative, 1)[0] if

    # Construct new row (removed year/month/numeric_date/acceleration)
    new_row = {
        'months_since_start': months_since_start,
        'county_encoded': county_code,
        'ev_total_lag1': lag1,
        'ev_total_lag2': lag2,
        'ev_total_lag3': lag3,
        'ev_total_roll_mean_3': roll_mean,
        'ev_total_pct_change_1': pct_change_1,
        'ev_total_pct_change_3': pct_change_3,
        'ev_growth_slope': ev_growth_slope
    }

    # Predict
    X_new = pd.DataFrame([new_row])[features]
    pred = model.predict(X_new)[0]
    new_row['Electric Vehicle (EV) Total'] = pred

    # Update rolling histories
    historical_ev.append(pred)
    if len(historical_ev) > 6:
        historical_ev.pop(0)

    cumulative_ev.append(cumulative_ev[-1] + pred)
    if len(cumulative_ev) > 6:
        cumulative_ev.pop(0)

    future_rows.append({
        'Date': next_date,
        'Electric Vehicle (EV) Total': pred,
        'months_since_start': months_since_start,
        'Source': 'Forecast'
    })
```

```
    latest_row['year'], latest_row['month'] = y, m

# Forecast DataFrame
forecast_df = pd.DataFrame(future_rows)

# Combine and plot
historical['Date'] = pd.to_datetime(historical[['year', 'month']].assign(day=1))
historical = historical[['Date', 'Electric Vehicle (EV) Total', 'months_since_start', 'Sour
combined = pd.concat([historical, forecast_df], ignore_index=True)

# Plot
plt.figure(figsize=(12, 6))
for source, group in combined.groupby('Source'):
    plt.plot(group['Date'], group['Electric Vehicle (EV) Total'], label=source,
             marker='o' if source == 'Forecast' else '.', linestyle='-' if source == 'Forec

plt.title(f"EV Adoption Forecast vs Historical - {county} County (Monthly Forecast for 3 Ye
plt.xlabel("Date")
plt.ylabel("EV Count")
plt.grid(True)
plt.legend()
plt.tight_layout()
plt.show()
```

County 'Kings' encoded as 130.



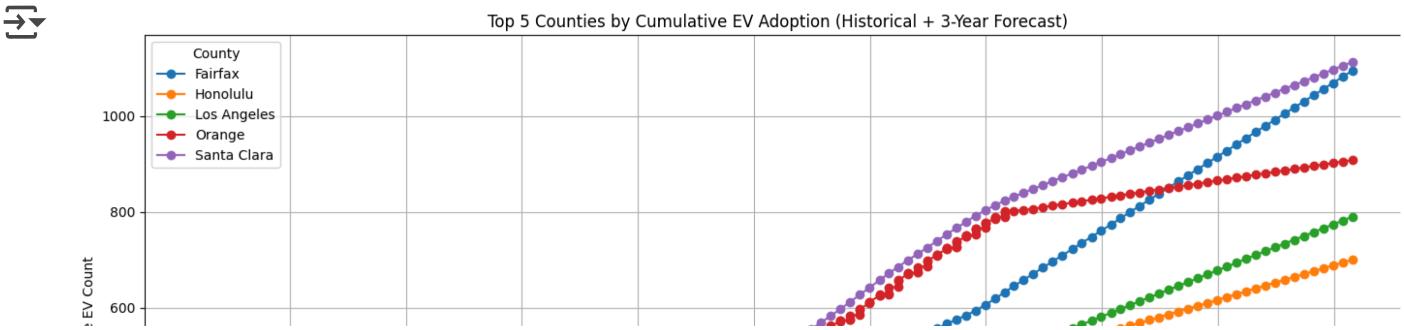

```
# --- Sort by date to ensure proper cumulative behavior ---
combined = combined.sort_values("Date")

# --- Calculate cumulative EV count ---
combined['Cumulative EVs'] = combined['Electric Vehicle (EV) Total'].cumsum()

# --- Plot cumulative EV adoption ---
plt.figure(figsize=(12, 6))
for source, group in combined.groupby('Source'):
    plt.plot(group['Date'], group['Cumulative EVs'], label=f'{source} (Cumulative)',
             marker='o' if source == 'Forecast' else '.', linestyle='-' if source == 'Forec

plt.title(f"Cumulative EV Adoption - {county} County")
plt.xlabel("Date")
plt.ylabel("Cumulative EV Count")
plt.grid(True)
plt.legend()
plt.tight_layout()
plt.show()
```




```
forecast_horizon = 36  # 3 years = 36 months

all_combined = []
unique_counties = df['County'].dropna().unique()

for county in unique_counties:
    try:
        county_code = le.transform([county])[0]
    except ValueError:
        continue

    county_df = df[df['county_encoded'] == county_code].sort_values("numeric_date")
    if county_df.empty or county_df.shape[0] < 6:
        continue

    # Extract initial months_since_start
    months_since_start = county_df['months_since_start'].max()

    historical = county_df[['Date', 'Electric Vehicle (EV) Total', 'months_since_start']].
    historical['Source'] = 'Historical'
    historical['County'] = county

    historical_ev = list(county_df['Electric Vehicle (EV) Total'].values[-6:])
    cumulative_ev = list(np.cumsum(historical_ev))
    slope_history = []

    future_rows = []

    for _ in range(forecast_horizon):
        months_since_start += 1

        lag1, lag2, lag3 = historical_ev[-1], historical_ev[-2], historical_ev[-3]
        roll_mean = np.mean([lag1, lag2, lag3])
        pct_change_1 = (lag1 - lag2) / lag2 if lag2 != 0 else 0
        pct_change_3 = (lag1 - lag3) / lag3 if lag3 != 0 else 0

        recent_cumulative = cumulative_ev[-6:]
        ev_growth_slope = np.polyfit(range(len(recent_cumulative)), recent_cumulative, 1)[

        # Optional: track slope history for acceleration (not used here)
        slope_history.append(ev_growth_slope)
        if len(slope_history) > 2:
            slope_history.pop(0)

        new_row = {
            'months_since_start': months_since_start,
            'county_encoded': county_code,
            'ev_total_lag1': lag1,
            'ev_total_lag2': lag2,
```

```
            'ev_total_lag3': lag3,
            'ev_total_roll_mean_3': roll_mean,
            'ev_total_pct_change_1': pct_change_1,
            'ev_total_pct_change_3': pct_change_3,
            'ev_growth_slope': ev_growth_slope
        }
# Predict
        X_new = pd.DataFrame([new_row])[features]
        pred = model.predict(X_new)[0]
        new_row['Electric Vehicle (EV) Total'] = pred

        # Store for plotting
        forecast_date = historical['Date'].max() + pd.DateOffset(months=len(future_rows) +
        future_rows.append({
            'Date': forecast_date,
            'Electric Vehicle (EV) Total': pred,
            'months_since_start': months_since_start,
            'County': county,
            'Source': 'Forecast'
        })

        # Update EV history
        historical_ev.append(pred)
        if len(historical_ev) > 6:
            historical_ev.pop(0)

        cumulative_ev.append(cumulative_ev[-1] + pred)
        if len(cumulative_ev) > 6:
            cumulative_ev.pop(0)

    forecast_df = pd.DataFrame(future_rows)
    combined = pd.concat([historical, forecast_df], ignore_index=True)
    combined = combined.sort_values("Date")
    combined['Cumulative EVs'] = combined['Electric Vehicle (EV) Total'].cumsum()

    all_combined.append(combined)
# Combine all counties
full_df = pd.concat(all_combined)

# Get final cumulative EV count per county
final_totals = full_df.groupby('County')['Cumulative EVs'].max().sort_values(ascending=Fal
top_5_counties = final_totals.head(5).index.tolist()

# Filter top 5 counties
top_5_df = full_df[full_df['County'].isin(top_5_counties)]

# Plot
plt.figure(figsize=(14, 7))
for county, group in top_5_df.groupby('County'):
    plt.plot(group['Date'], group['Cumulative EVs'], label=county, marker='o')

# Format x-axis to show one tick per year
plt.title("Top 5 Counties by Cumulative EV Adoption (Historical + 3-Year Forecast)")
plt.xlabel("Date")
plt.ylabel("Cumulative EV Count")
plt.grid(True)
plt.legend(title="County")
plt.xticks(
    ticks=pd.date_range(start=top_5_df['Date'].min(), end=top_5_df['Date'].max(), freq='YS
    labels=[str(d.year) for d in pd.date_range(start=top_5_df['Date'].min(), end=top_5_df[
```

```
    rotation=0
)
plt.tight_layout()
plt.show()
```




```
import joblib

# Save the trained model to file
```