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# STRATEGY FOR EV AND EV CHARGING STATIONS

General Motors



Presented by  
**Jack Hu,**  
**Haoxiang Yi,**  
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**Boyuan Lu**



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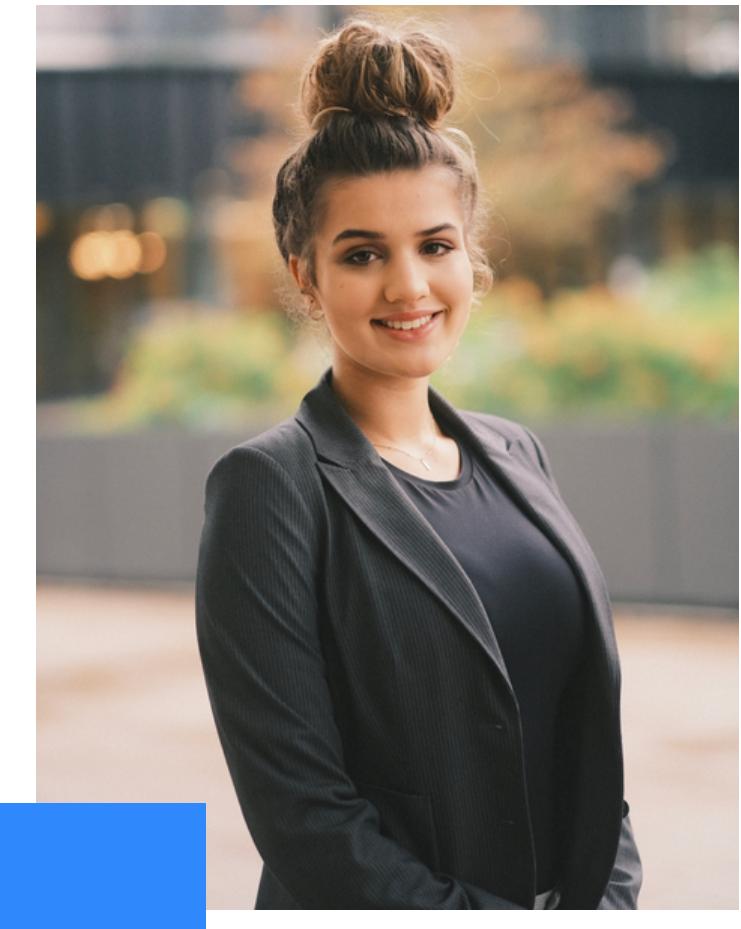
# OUR TEAM



JACK HU



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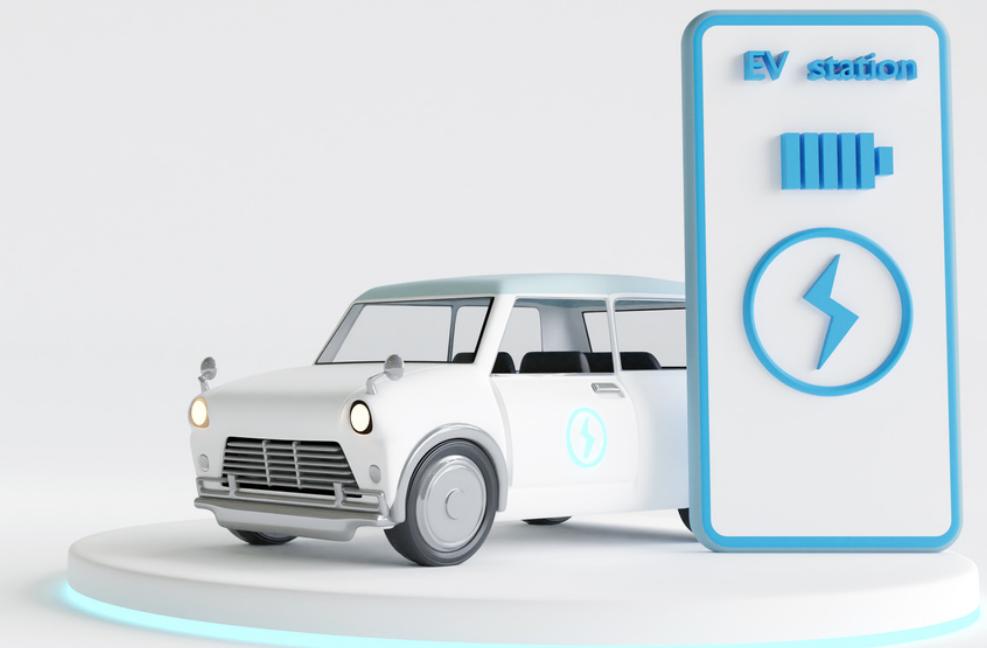


JAIDA ADAMSON



BOYUAN LU

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# BACKGROUND

## EXPLORATION OF VARIABLES INFLUENCING ELECTRIC VEHICLE (EV) ADOPTION AND CHARGER PLACEMENT.

Key Questions to Answer:

- 1.What are the factors that contribute to EV adoption, and what role does charging infrastructure play?
- 2.What areas (zip codes) should see the most growth if new EV chargers are installed?
- 3.Where specifically (venues) within the highest priority areas should EV chargers be installed?



# APPROACH

**Defining the target variables:**

EV Adoption Rate:

- Predict based on all useful variables
- Identify most significant variables affecting adoption
- Determine the best ways to promote EVs

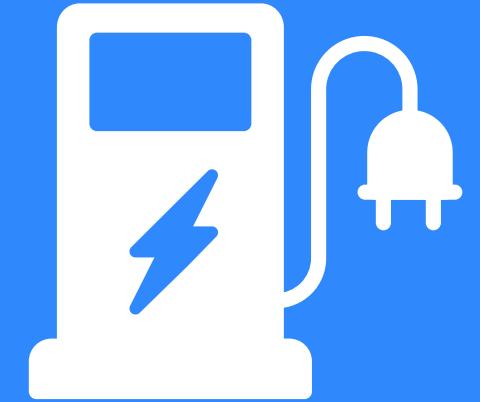


# APPROACH

## Defining the target variables:

### Charging Stations Count:

- Predict based on all useful variables
- Identify the most significant variables affecting number of charging stations and use it determine the most influential venues
- Focus on the top 100 zip codes with the largest differences between predicted and actual
- Analyze the top 100 zip codes and find the best way to allocate the 100 charging stations based on the marginal increase in EV adoption rate

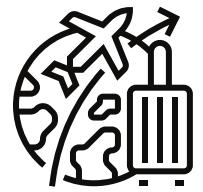


# DATA COLLECTION

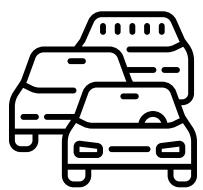
## DATA SOURCES:



1. WEATHER INFORMATION
  - AVERAGE PRECIPITATION, TEMPERATURE PER ZIP CODE



3. TOURIST-RELATED INFORMATION
  - NUMBER OF TOURISTS, HOTELS PER ZIP CODE/COUNTY



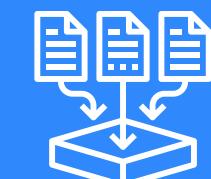
4. TRAFFIC-RELATED DATA
  - NUMBER OF MAJOR ROADS, TRANSIT PLACES PER ZIP CODE/COUNTY



5. CHARGING STATIONS
  - LOCATIONS AND COUNTS OF PUBLIC AND PRIVATE CHARGING STATIONS



6. VENUE DATA
  - NUMBER OF RETAIL, OFFICES, PARKING, MEDICAL/EDUCATIONAL PER ZIP CODE/COUNTY



# DATA TRANSFORMATION

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01

## Data Cleaning and Preprocessing

- Grouped data by county or zip code level
- Combined main data provided by the client with additional influential data

02

## Missing Value Handling

- Grouped by county and found the average to fill in some missing variables
- Created dummy variables for categorical variables

03

## Data Integration

- Filtered data for the chosen state: **Texas**
- Ensured consistency when combining datasets

04

## Feature Engineering

- Developed new columns to better explain target variables, such as "charging stations per EV"

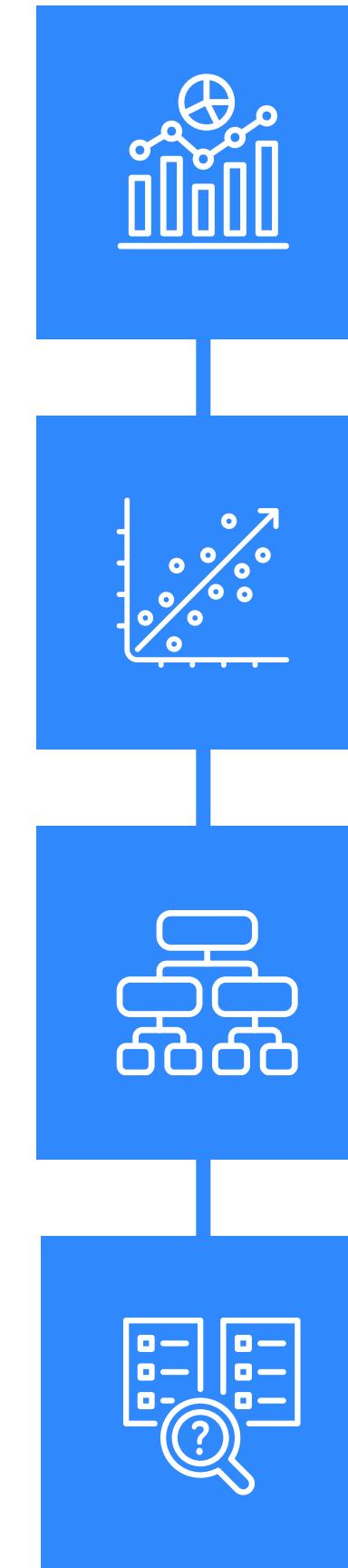


**LINEAR REGRESSION**

**RANDOM FOREST**

**MODEL  
EVALUATION**

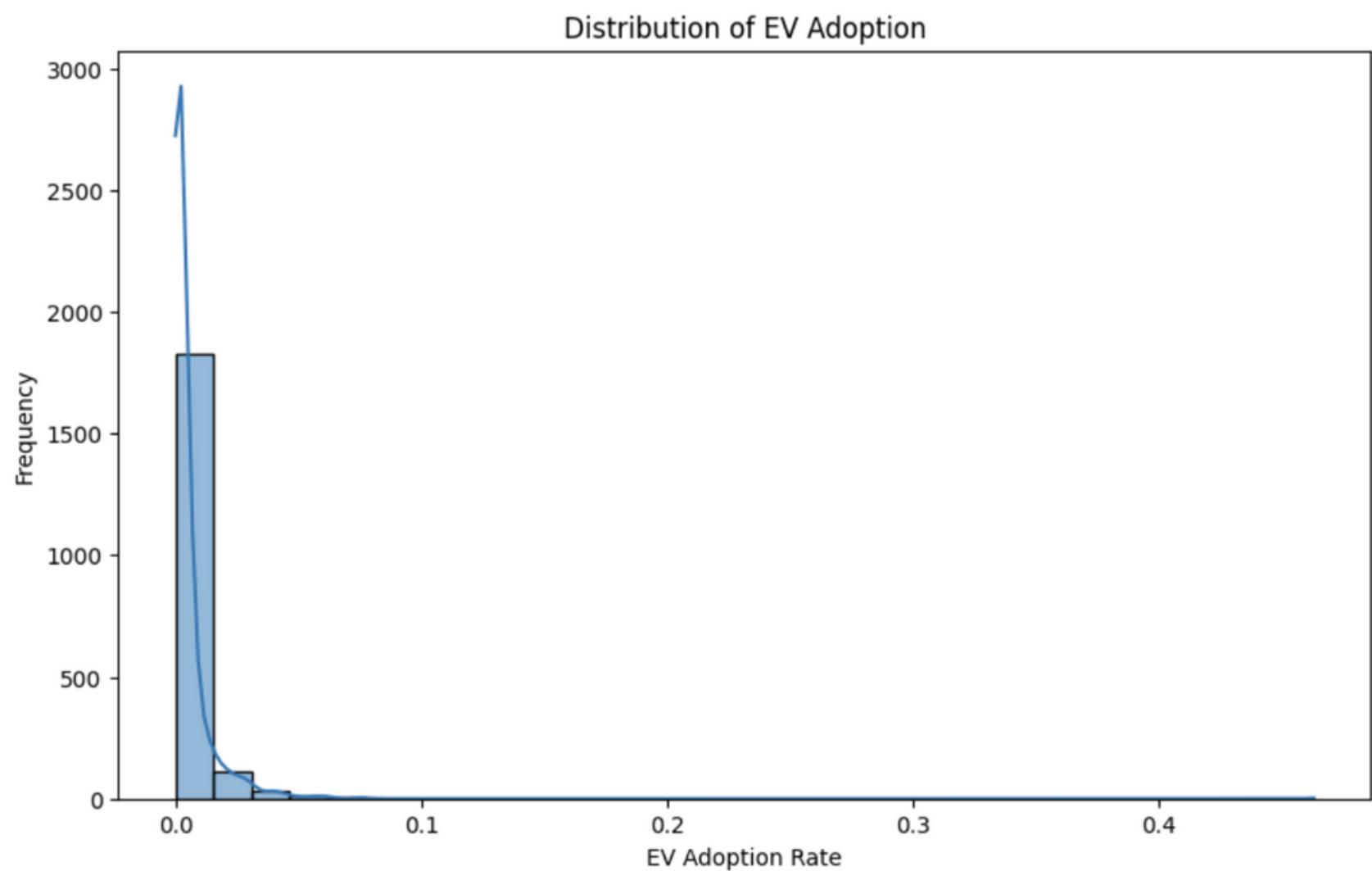
**EDA**



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**EV  
ADOPTION  
RATE  
MODELING**

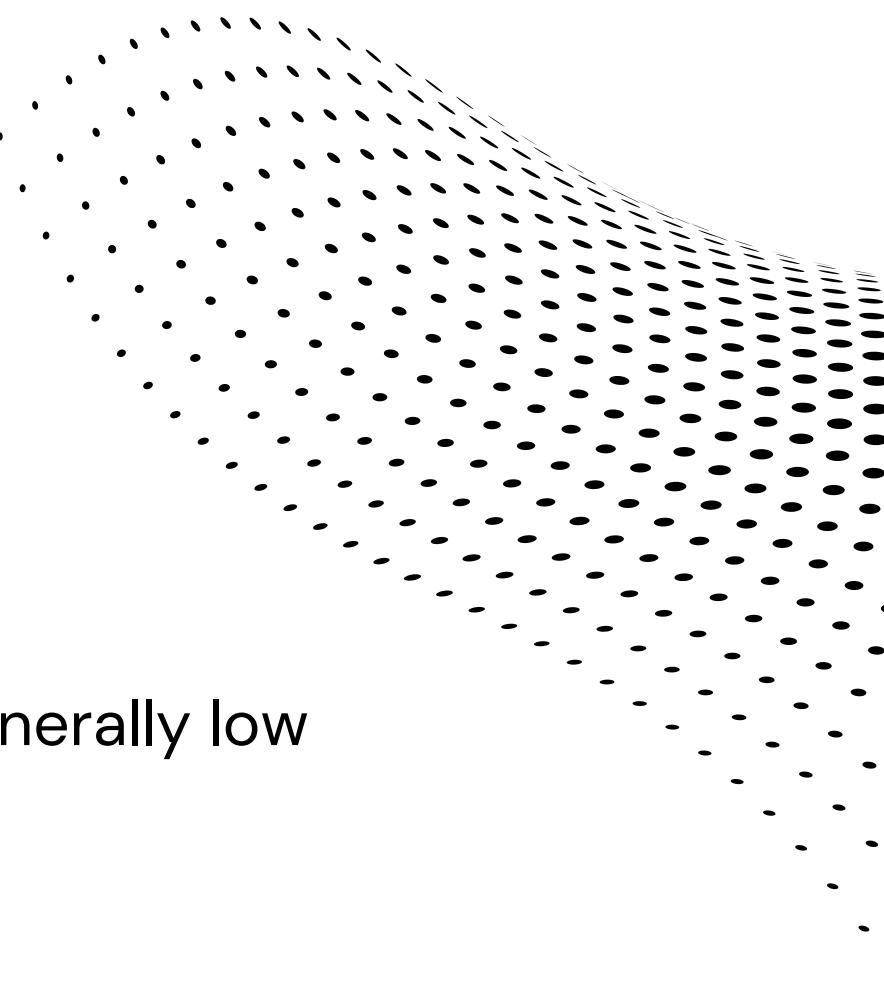
# EDA



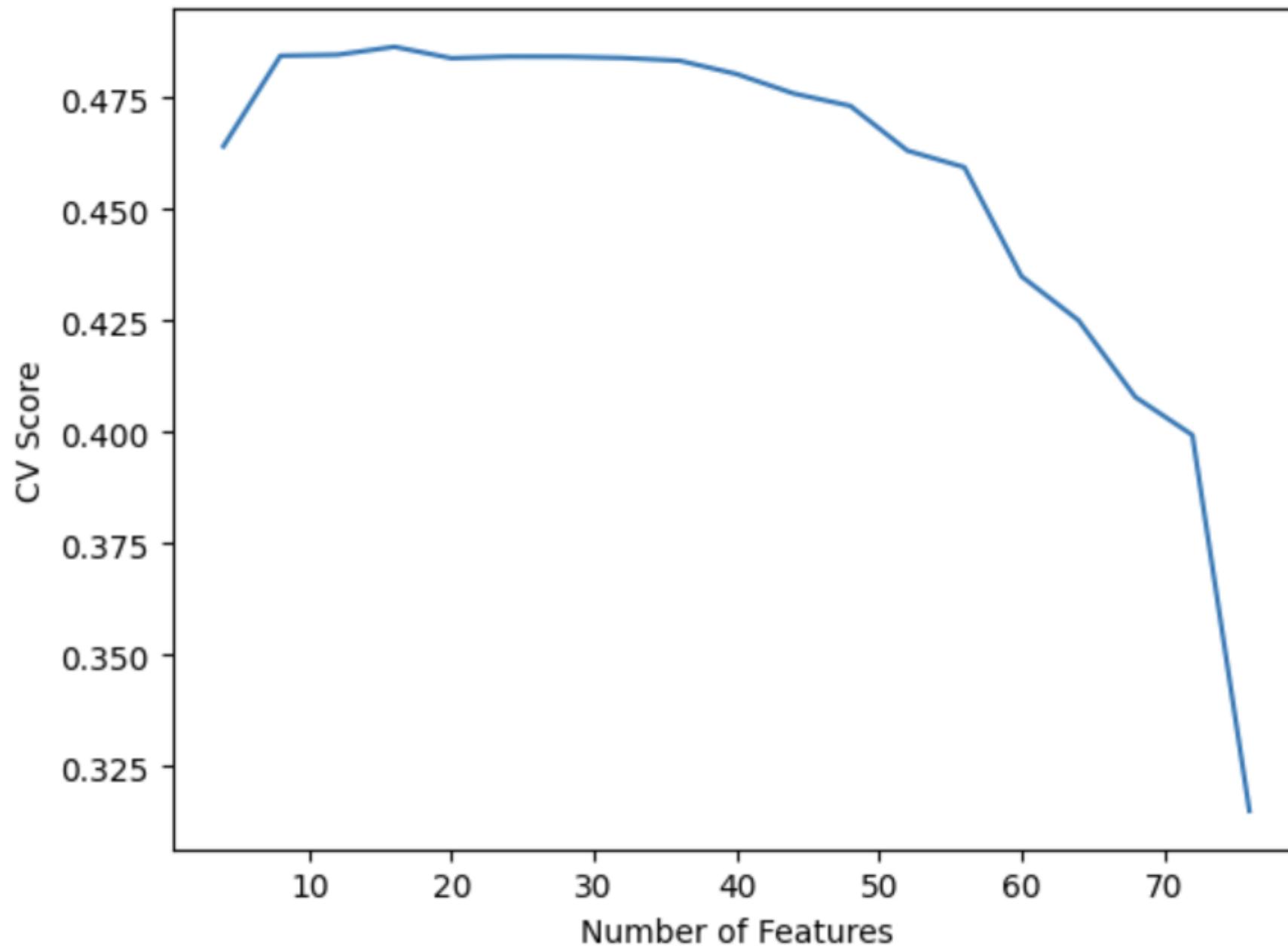
Highly skewed distribution

Adoption rate of EVs is generally low

Applying a logarithmic scale to the data



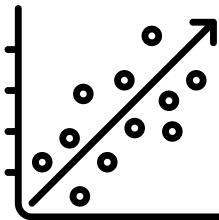
# LINEAR REGRESSION



The CV score starts at a relatively high value when the number of features is small (near 4), which suggests that a few features are already providing a significant amount of predictive power.

The most significant drop happens after approximately 50 features

Optimal number of features for linear regression: 16

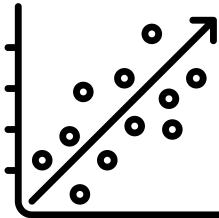


# LINEAR REGRESSION

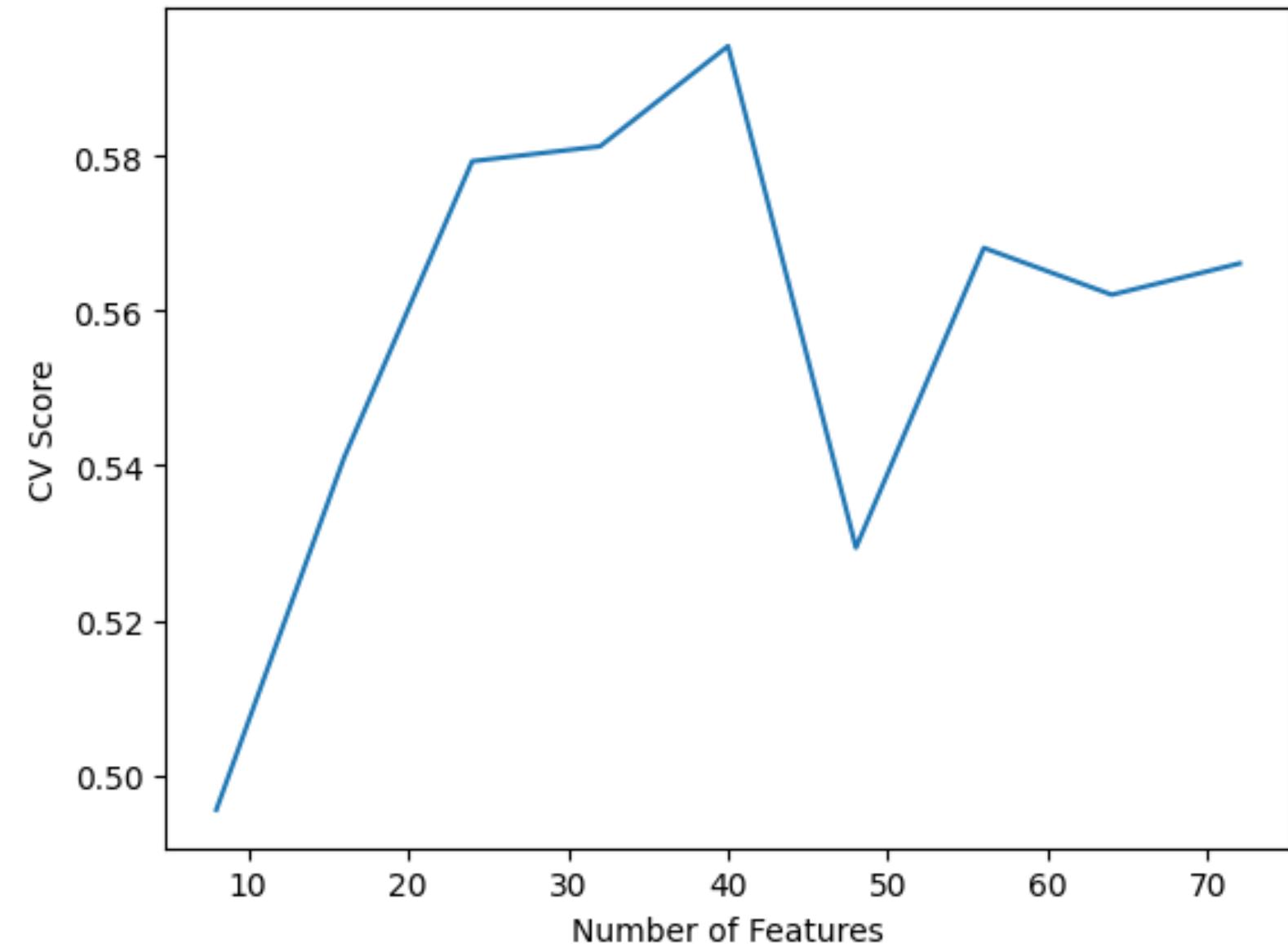
wfh_rate	2.670000e-02
Total_EV_Chargers	2.000000e-04
Total_Hotel_Airbnb	8.789000e-07
individual_income_percapita	1.192000e-07
household_income_median	5.988000e-08
RUCC_2013	-3.000000e-04

R-squared value: 0.7321320282984156

Mean squared error (MSE) is 1.59e-05



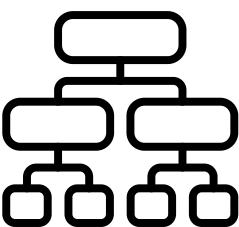
# RANDOM FOREST



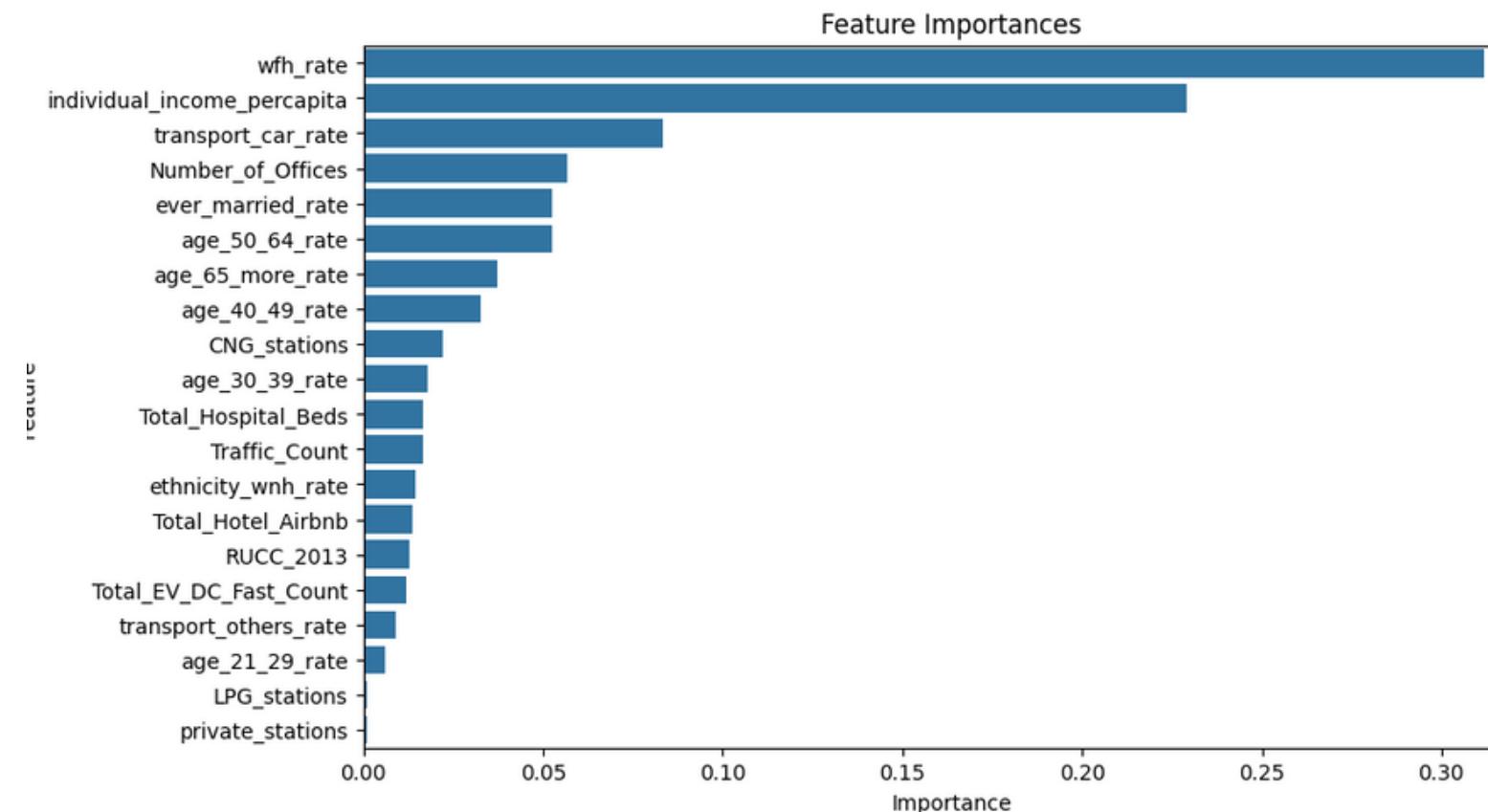
Optimal number of features for  
random forest: 40

cv score of 0.5942108029867018

R-squared value for training data:  
0.8884544338686554

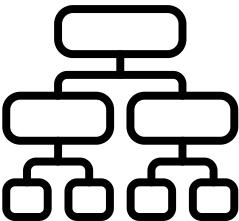


# MODEL EVALUATION

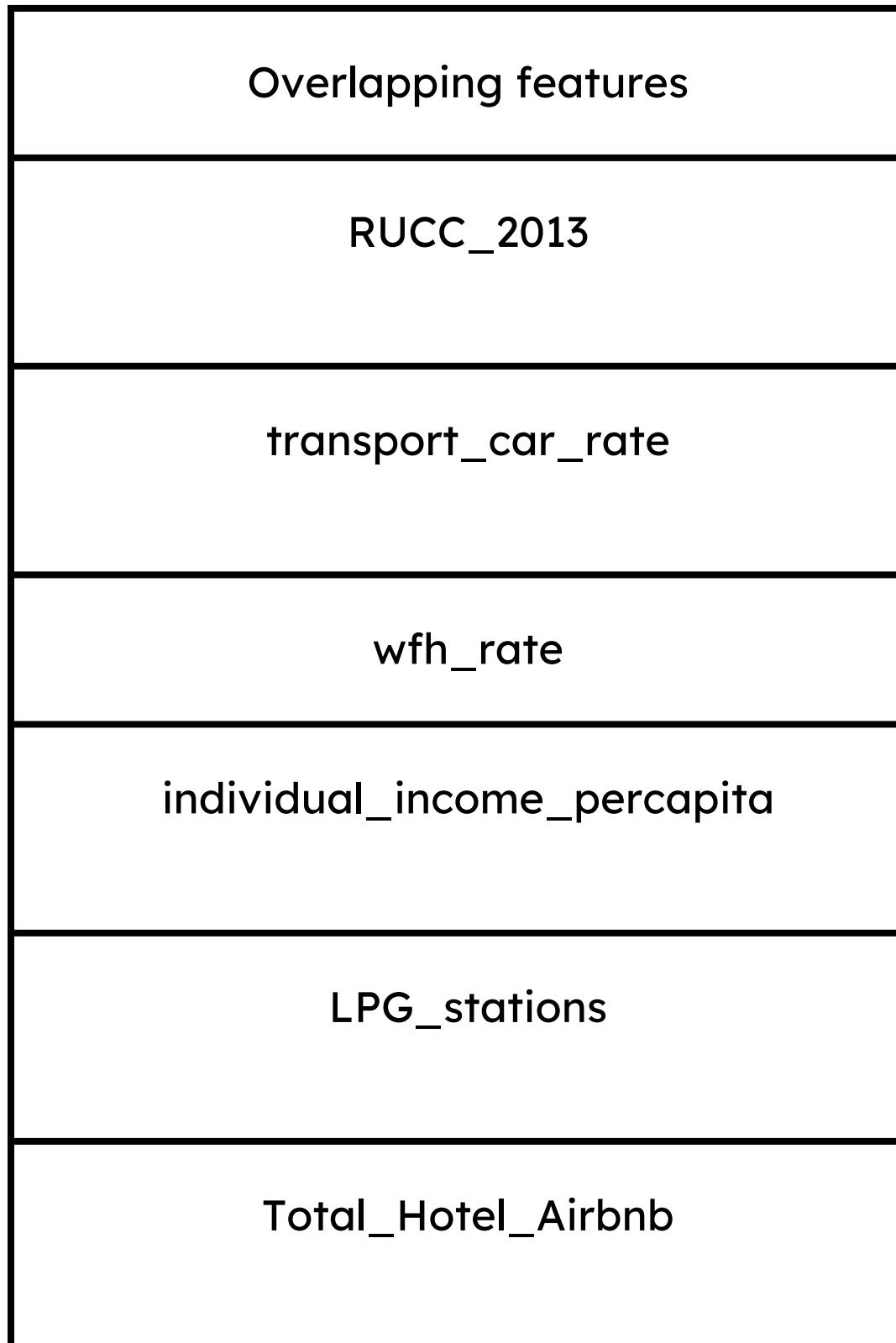


	Linear Regression	Random Forest
R-squared	0.7321	0.73207
MSE	1.590716e-05	1.591030e-05

- Performance: Both models perform equally well on the test set.
- Complexity: The Linear Regression model is generally simpler and faster to train than a Random Forest, and it offers the advantage of interpretability.
- Deployment: For deployment considerations, simplicity and speed can be advantageous.



# MODEL COMPARISON



- **Policy Implications:**
  - RUCC\_2013
  - Transport\_car\_rate
  - WFH\_rate
- **Economic Considerations:**
  - Individual\_income\_percapita
  - LPG\_stations
- **Tourism**
  - Total\_Hotel\_Airbnb
- **These overlapping features can help in crafting nuanced approaches to promote EVs, considering the diversity in demographics and economic conditions.**



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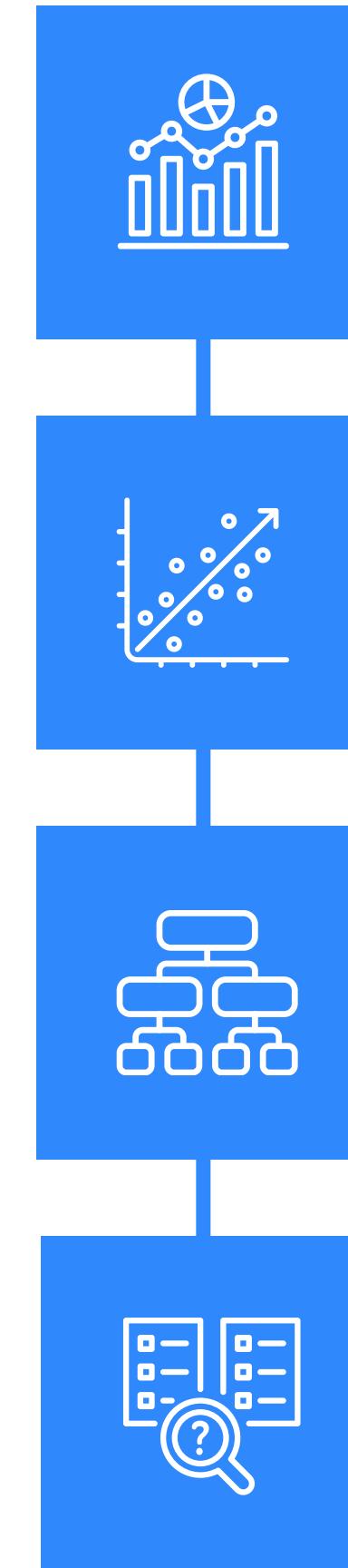
# NUMBER OF CHARGERS MODELING

LINEAR REGRESSION

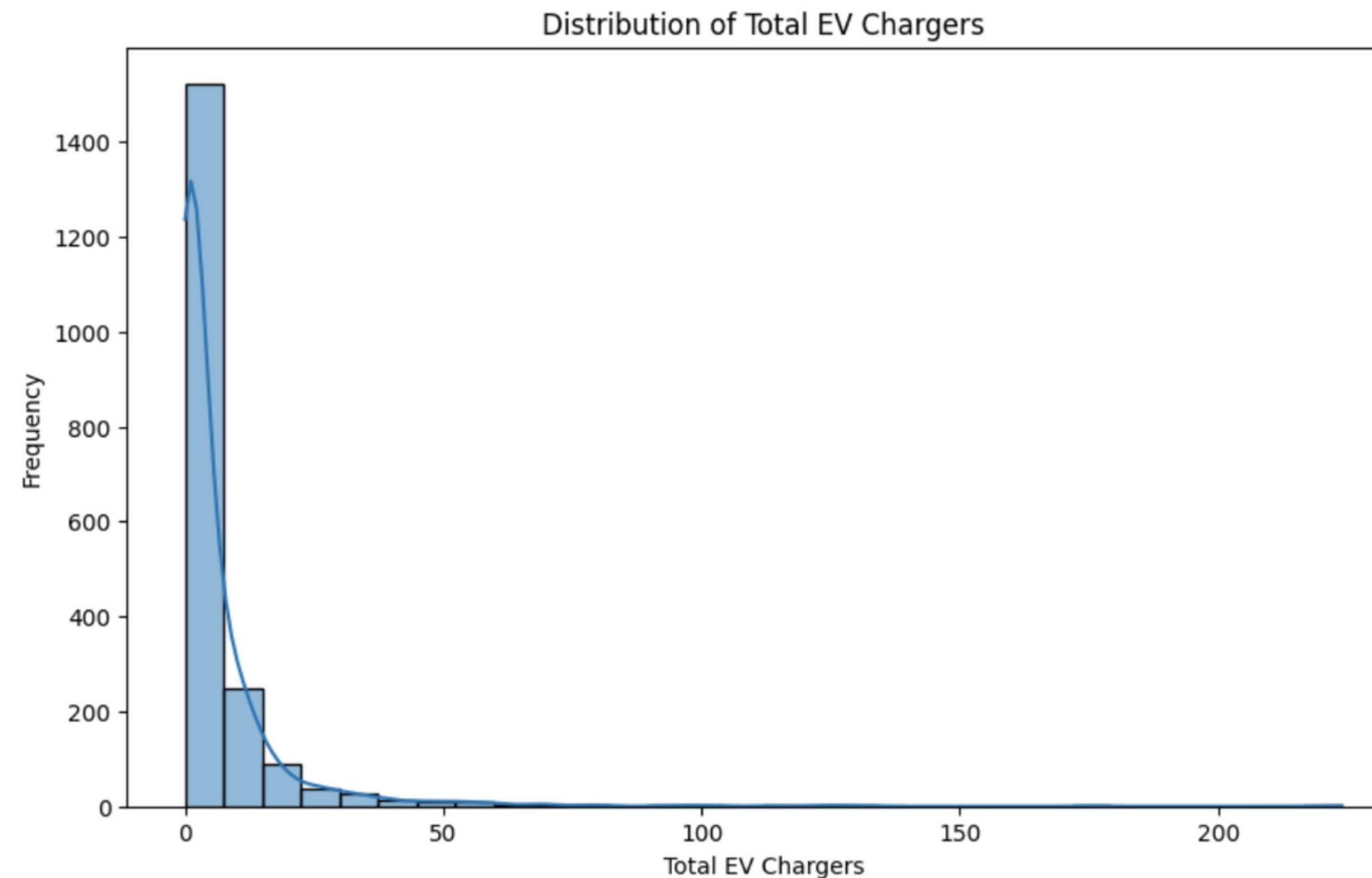
RANDOM FOREST

MODEL  
EVALUATION

EDA



# EDA



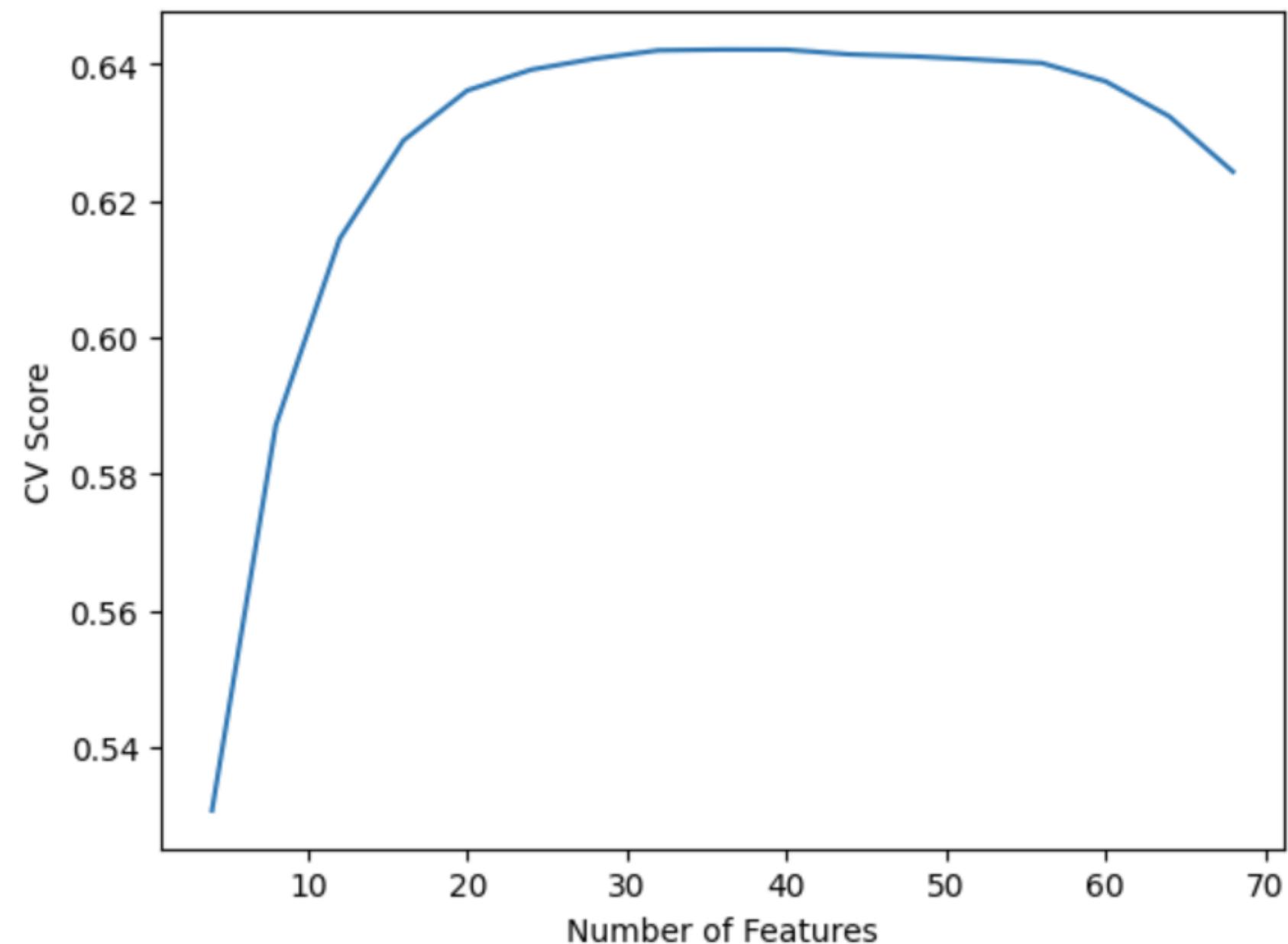
Highly skewed distribution

The number of EV Chargers is low

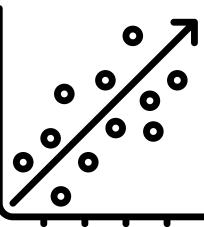
Applying logarithmic transformation



# LINEAR REGRESSION



Optimal number of features for linear regression: 36



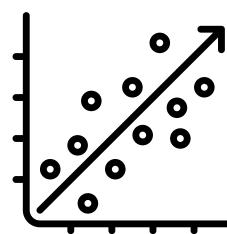
# LINEAR REGRESSION

		coef	std err	t	P> t	[0.025	0.975]
	transport_public_rate	1.181300e+01	2.656000e+00	4.447	0.000	6.603000e+00	1.702300e+01
	Most_Common_Charging_Facility_Type_TRAVEL_CENTER	1.949900e+00	3.290000e-01	5.921	0.000	1.304000e+00	2.596000e+00
	age_21_29_rate	1.868000e+00	2.680000e-01	6.974	0.000	1.343000e+00	2.393000e+00
	Most_Common_Charging_Facility_Type_PAY GARAGE	1.836900e+00	6.580000e-01	2.790	0.005	5.460000e-01	3.128000e+00
	Most_Common_Charging_Facility_Type_PUBLIC	1.827400e+00	4.650000e-01	3.928	0.000	9.150000e-01	2.740000e+00
	Most_Common_Charging_Facility_Type_AIRPORT	1.806100e+00	5.170000e-01	3.494	0.000	7.920000e-01	2.820000e+00
	Most_Common_Charging_Facility_Type_GROCERY	1.679800e+00	4.660000e-01	3.603	0.000	7.650000e-01	2.594000e+00
	Most_Common_Charging_Facility_Type_GAS_STATION	1.500900e+00	1.390000e-01	10.777	0.000	1.228000e+00	1.774000e+00
	age_30_39_rate	1.313500e+00	3.360000e-01	3.913	0.000	6.550000e-01	1.972000e+00
	Most_Common_Charging_Facility_Type_OTHER	8.589000e-01	1.510000e-01	5.704	0.000	5.640000e-01	1.154000e+00
	Most_Common_Charging_Facility_Type_HOSPITAL	8.161000e-01	3.820000e-01	2.136	0.033	6.700000e-02	1.566000e+00
	Most_Common_Charging_Facility_Type_CAR DEALER	7.933000e-01	9.700000e-02	8.200	0.000	6.040000e-01	9.830000e-01
	Most_Common_Charging_Facility_Type_SHOPPING CENTER	7.725000e-01	1.530000e-01	5.036	0.000	4.720000e-01	1.073000e+00
	Most_Common_Charging_Facility_Type_FED GOV	7.633000e-01	2.100000e-01	3.630	0.000	3.510000e-01	1.176000e+00

28 significant variables

Testing R-squared value of 0.718

Mean Squared Error (MSE) is 0.621



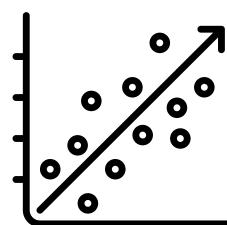
# LINEAR REGRESSION

		coef	std err	t	P> t	[0.025	0.975]
	age_0_20_rate	7.304000e-01	1.830000e-01	3.982	0.000	3.710000e-01	1.090000e+00
	Most_Common_Charging_Facility_Type_HOTEL	7.272000e-01	6.500000e-02	11.251	0.000	6.000000e-01	8.540000e-01
	Most_Common_Charging_Facility_Type_MUNI_GOV	6.565000e-01	3.300000e-01	1.990	0.047	9.000000e-03	1.304000e+00
	Most_Common_Charging_Facility_Type_OFFICE_BLDG	5.472000e-01	2.110000e-01	2.594	0.010	1.330000e-01	9.610000e-01
	age_65_more_rate	4.669000e-01	2.120000e-01	2.197	0.028	5.000000e-02	8.840000e-01
	Most_Common_Charging_Facility_Type_PARKING_LOT	4.398000e-01	2.200000e-01	1.995	0.046	7.000000e-03	8.720000e-01
	three_year_precipitation_avg	4.810000e-02	1.800000e-02	2.659	0.008	1.300000e-02	8.400000e-02
	Total_EV	4.000000e-04	7.720000e-05	5.307	0.000	0.000000e+00	1.000000e-03
	Total_Hotel_Airbnb	2.000000e-04	3.820000e-05	5.402	0.000	0.000000e+00	0.000000e+00
	individual_income_per capita	1.135000e-05	1.470000e-06	7.708	0.000	8.460000e-06	1.420000e-05
	total_population	6.179000e-06	1.420000e-06	4.342	0.000	3.390000e-06	8.970000e-06
	Traffic_Count	-5.931000e-09	2.240000e-09	-2.652	0.008	-1.030000e-08	-1.540000e-09
	RUCC_2013	-8.790000e-02	9.000000e-03	-10.145	0.000	-1.050000e-01	-7.100000e-02
	ethnicity_wnh_rate	-3.099000e-01	9.200000e-02	-3.362	0.001	-4.910000e-01	-1.290000e-01

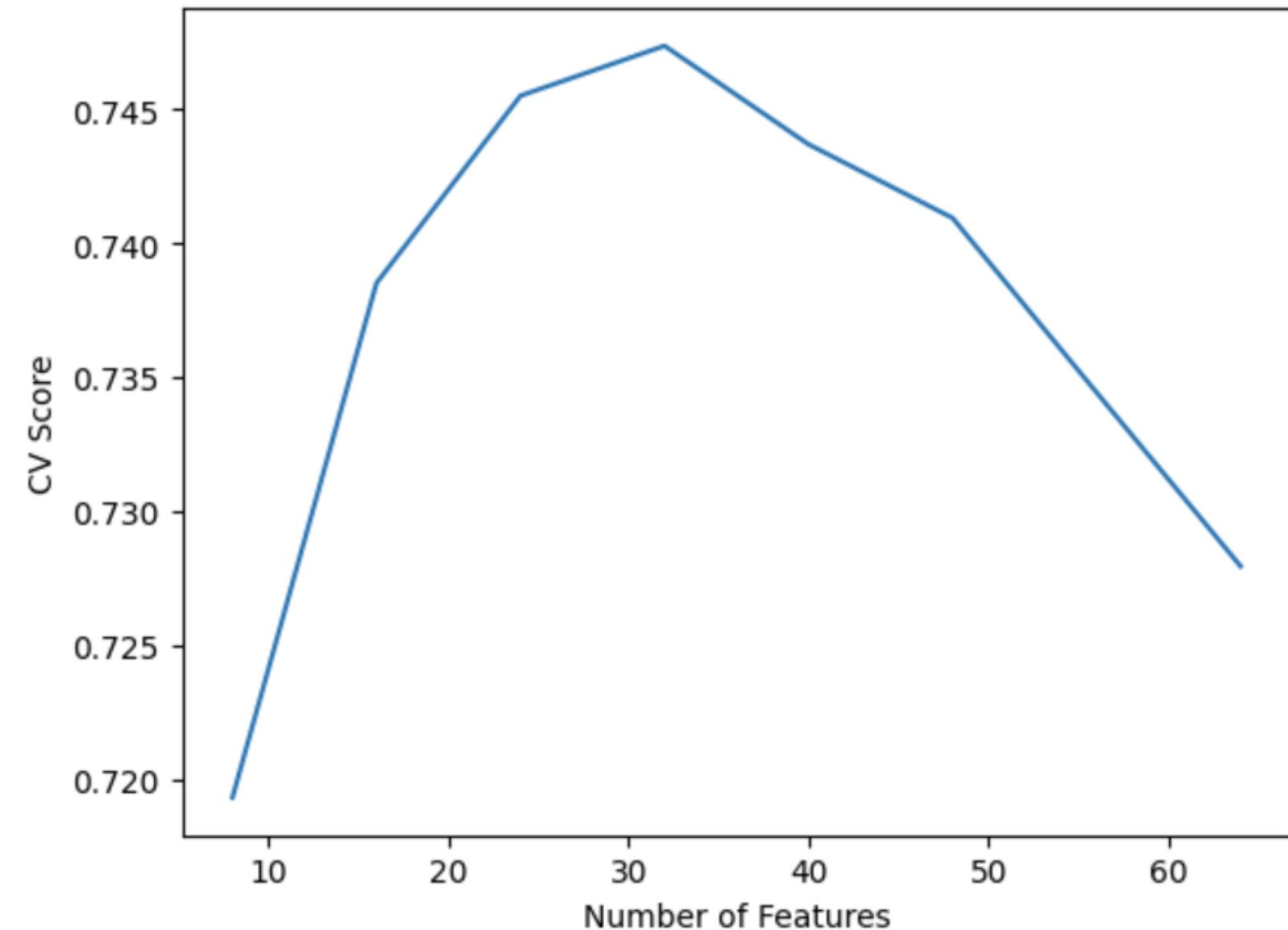
28 significant variables

Testing R-squared value of 0.718

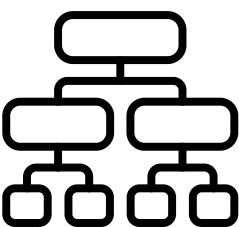
Mean Squared Error (MSE) is 0.621



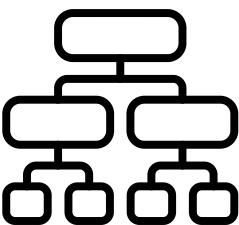
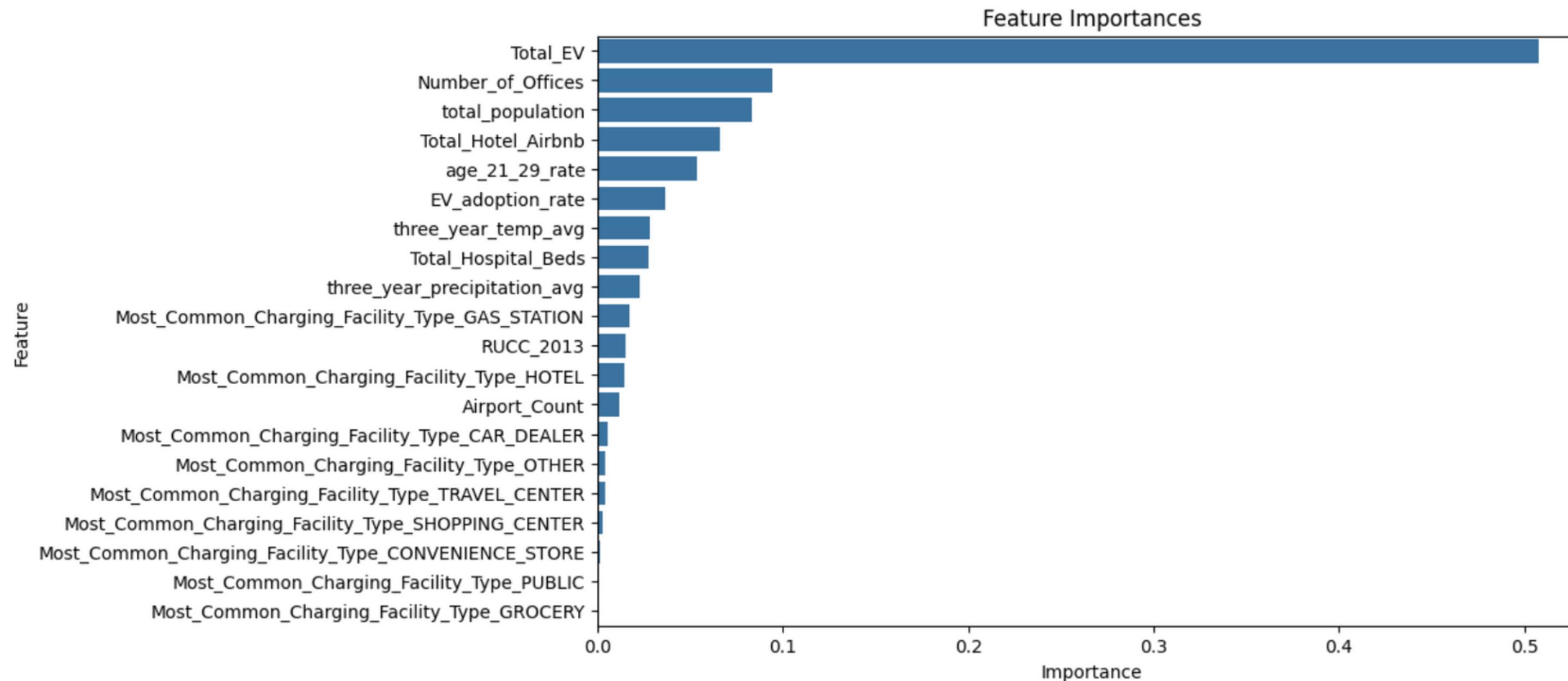
# RANDOM FOREST



Optimal number of features for random forest: 32

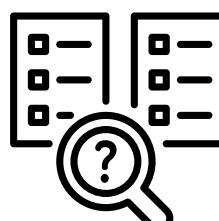


# RANDOM FOREST



# MODEL COMPARISON

RUCC_2013	<b>Most_Common_Charging_Facility_Type_CAR DEALER</b>
total_population	<b>Most_Common_Charging_Facility_Type_GAS_STATION</b>
age_21_29_rate	<b>Most_Common_Charging_Facility_Type_GROCERY</b>
Total_EV	<b>Most_Common_Charging_Facility_Type_HOTEL</b>
Total_Hotel_Airbnb	<b>Most_Common_Charging_Facility_Type_PUBLIC</b>
three_year_precipitation_avg	<b>Most_Common_Charging_Facility_Type_TRAVEL_CENTER</b>
three_year_temp_avg	<b>Most_Common_Charging_Facility_Type_SHOPPING_CENTER</b>



# MODEL COMPARISON

	R-Squared	MSE
Linear Regression	0.718	0.621
Random Forest	0.805	0.267



# MODEL EVALUATION

Zip Code	Difference
78206	8
78731	7
78751	7
78256	6
77006	6
77003	5
75025	5
75251	5
77407	4
75039	4

- Using the Random Forest model, we predicted the number of EV charging stations that each zip code should have
- Difference = Prediction - Actual
- Top 10 zip codes with the largest difference is shown here



# MARGINAL ANALYSIS



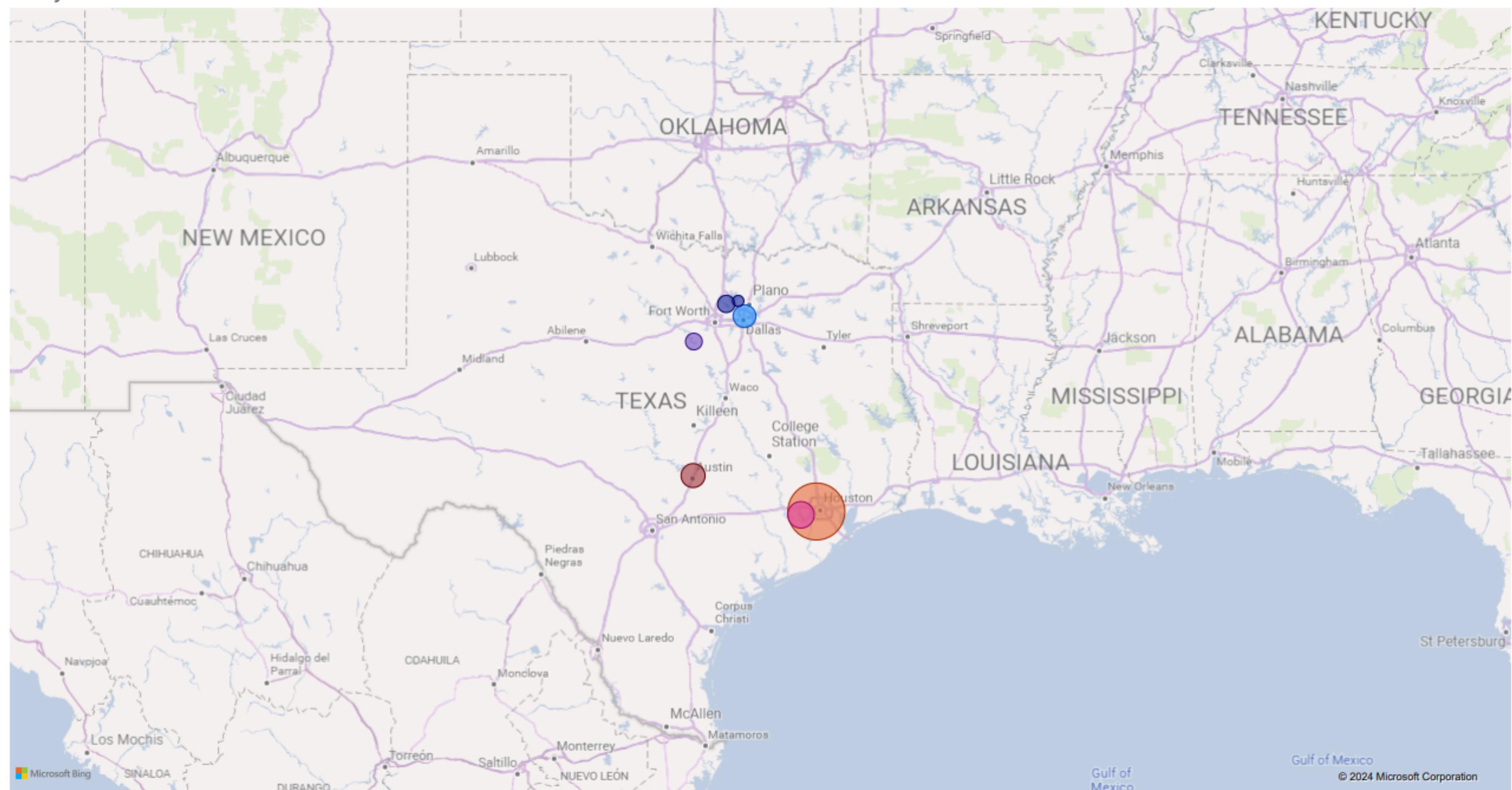
# WHERE TO PUT THE CHARGERS?

We ran random forest models iteratively to determine which ZIP codes show the greatest increase in EV adoption rates when additional charging stations are allocated one at a time.

ZIP	County	Current_Number_of_Charging_Stations	Additional_Charging_Stations	Increase_in_EV_Adoption_Rate
77046	Harris	10	67	0.388479862
78751	Travis	9	10	0.049241123
75206	Dallas	5	9	0.043053624
77407	Fort Bend	10	7	0.063810303
75022	Denton	1	3	0.019884357
76049	Hood	3	3	0.017847721
75056	Denton	21	1	0.00455626

## Increase\_in\_EV\_Adoption\_Rate by ZIP and County

**County** ● Dallas ● Denton ● Fort Bend ● Harris ● Hood ● Travis



# WHERE TO PUT THE CHARGERS?

Do these locations make sense?

ZIP	County	Number_of_Charging_Stations_per_EV	RUCC_2013
77046	Harris	0.416666667	1
78751	Travis	0.027108434	1
75206	Dallas	0.006849315	1
77407	Fort Bend	0.006666667	1
75022	Denton	0.001081081	1
76049	Hood	0.015789474	1
75056	Denton	0.014037433	1

# WHERE TO PUT THE CHARGERS?

What are the precise impacts?

9193 New EVs

\$53,376\* X 9193 =  
**\$491M  
REVENUE**

ZIP	County	Additional_Charging_Stations	Increase_in_EV_Adoption_Rate	Number_of_EVs_Added
77046	Harris	67	0.388479862	487.1537472
78751	Travis	10	0.049241123	803.9105747
75206	Dallas	9	0.043053624	1654.636864
77407	Fort Bend	7	0.063810303	4887.869181
75022	Denton	3	0.019884357	536.8776412
76049	Hood	3	0.017847721	522.9560853
75056	Denton	1	0.00455626	299.7335674

\*According to the 2023 Kelly Blue Book

# CONCLUSION

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## Q1 Factors Influencing EV Adoption Rate

- Urbanization
- Car Usage
- Life Style
- Income
- LPG Rate
- Hotel

## Q2 Where To Put the Chargers?

- 77046
- 78751
- 75206
- 77407
- 75022
- 76049
- 75056
- \$491M Revenue

## Q3 What Venue Specifically to Put the Chargers?

- Car Dealership
- Gas Station
- Grocery
- Hotel
- Public Parking Lot
- Travel Center
- Shopping Center