Placement Optimization of EV Charging Stations

Ketaki Santan, Sai Kiran Bavgi, Yusuf Khan, Kartik Dhawan, Niranjan Ramarajar

Summary

With the increasing adoption of Electric vehicles, a key factor in the development of smart city infrastructure will be identifying ***Optimal EV Charger locations***. To solve this problem, our study proposes a novel approach that combines machine learning, linear optimization algorithms, interactive visuals using ***kepler.gl***, and unique ***telematics data*** (half billion rows with over 200 features) provided by ***Honda R&D***

Telematics Data

The Koto API exposes data collected every 5 seconds from Honda Vehicles. We analyzed data collected over a time period of one month. We extracted useful features like VIN (Unique Identifier for each vehicle), Vehicle Latitude and Longitude, Car Sequence Number and Timestamp.

Methodology & Results

Data Engineering

1. Data Acquisition & cleaning
2. After performing our unsupervised learning for each identified cluster location, for each cluster we derived # total visits (**tv**), # unique visits (***uv***), avg. dwell time, diversity (***uv/tv***), arrival rate
3. Based on the above derived features we computed the cluster utility score
4. We utilized ***google maps API*** to generate a matrix hosting the trip distance b/w the ***cluster*** centers

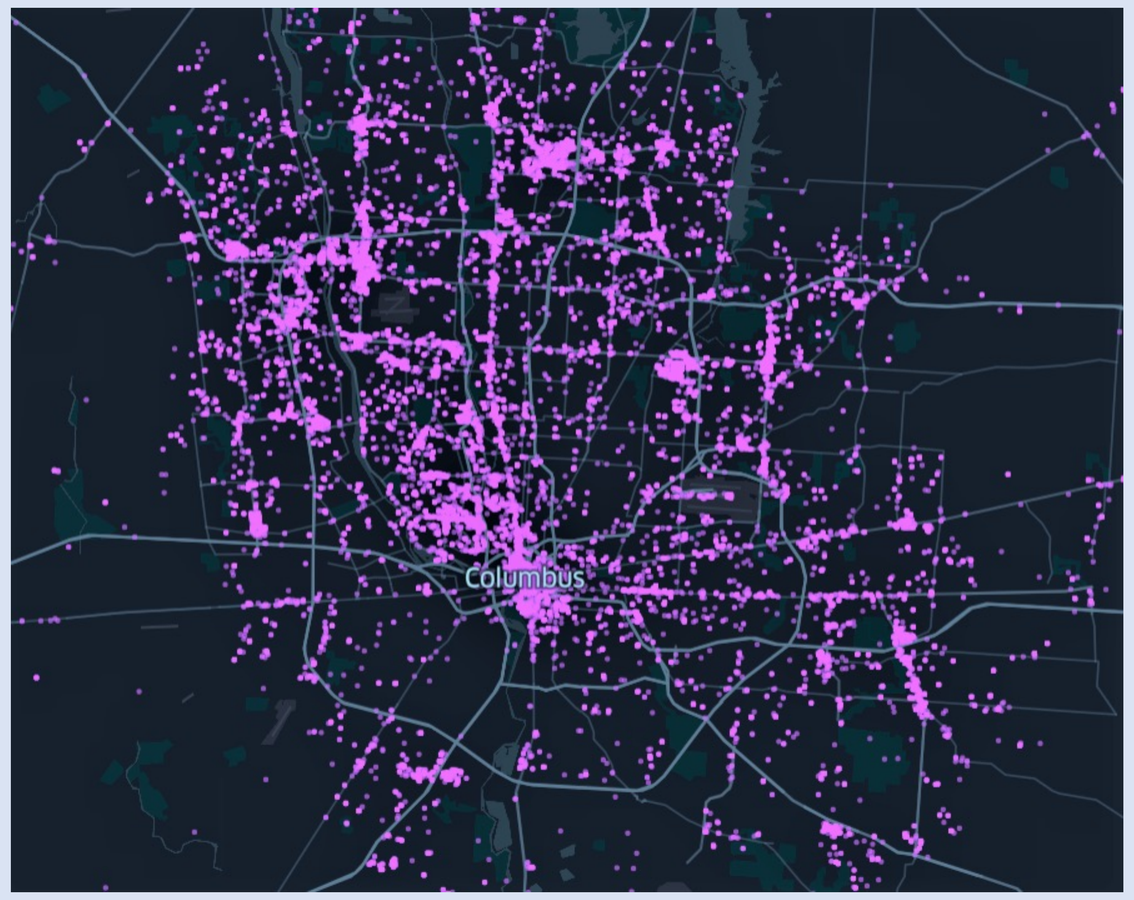

Figure (1): All destinations from our dataset highlighted in the city of Columbus

Unsupervised Learning

1. The cleaned data was passed through **DBSCAN** clustering algorithm that utilizes ***destination*** latitude and longitude to group destinations that are roughly 200m together
2. The derived utility score of each ***cluster*** is passed through our optimization formulation to identify locations for installing EV chargers

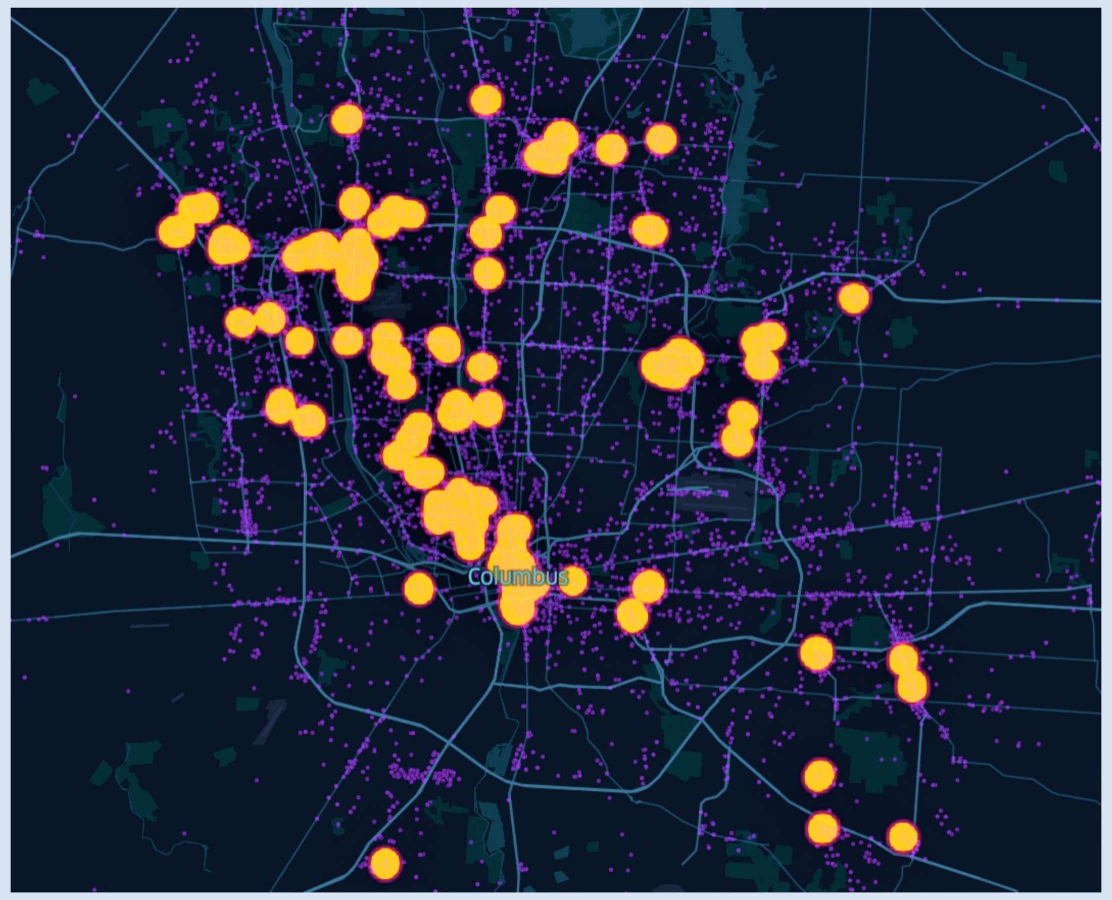

Figure (2): Identified clusters after DBSCAN

Linear Optimization Formulation

Decision Variables

$x_i \in \{0,1\} \quad \forall\, i = 1, \dots, n$ — **cluster centers**

$y_{ij} \in \{0,1\} \quad \forall\, i, j = 1, \dots, n \ and\ i < j$ — ***edges***

Optimization Function

$Min: \{\sum c x_i - \sum u_i x_i\}$ — ***Installation cost – Utility***

Constraints

$\sum c x_i \leq Budget \quad \forall\, i, j = 1, \dots, n$ — ***Budget Limit***

$$Threshold\ Dist \leq \frac{\sum d_{ij} y_{ij}}{\sum y_{ij}} \leq Avg.EV\ Range$$

Avg. Cluster dist. Limits

$$\frac{(x_i + x_j)}{2} - y_{ij} \leq 0.5$$

$$\frac{(x_i + x_j)}{2} - y_{ij} \leq 0$$

Nodes to Edges coupling constraint

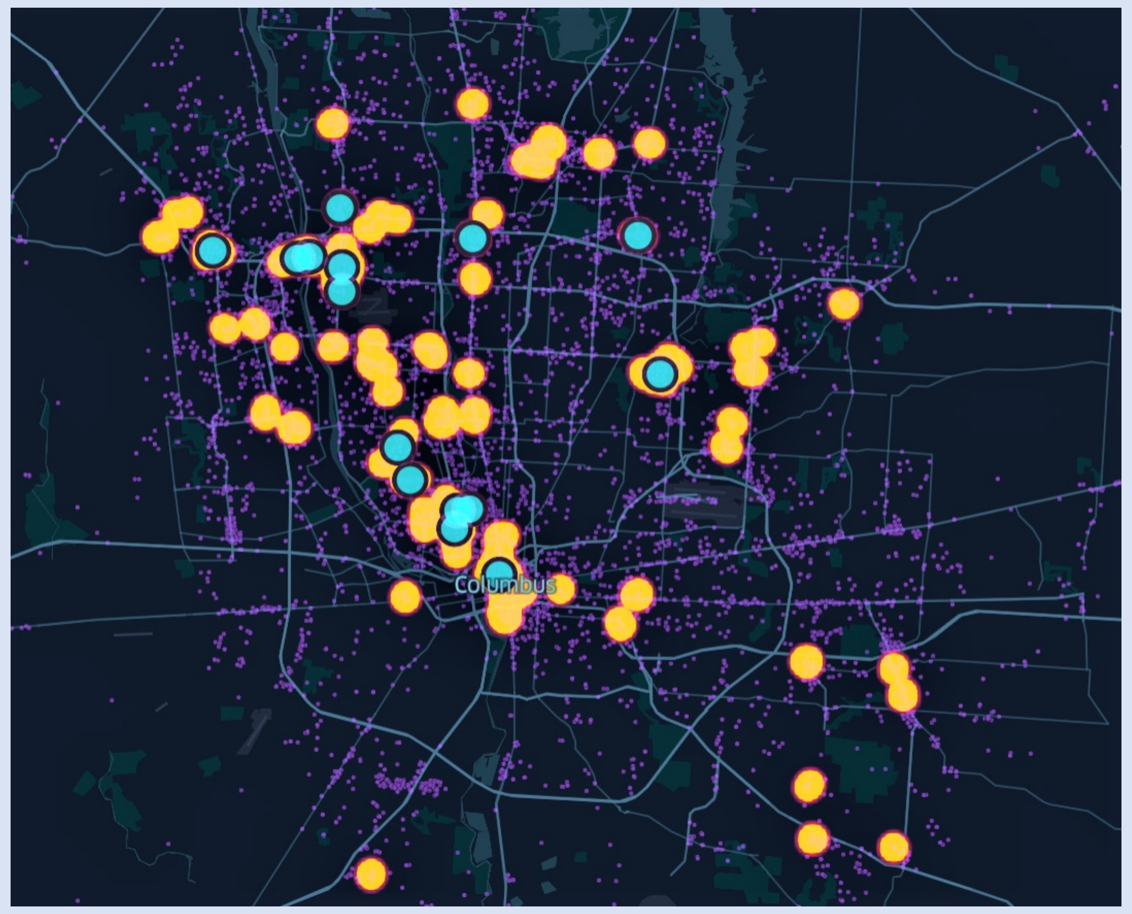

Figure (3): Optimal locations identified after running the optimization algorithm

Evaluation & Conclusions

1. Existing literature utilizes demographic information and focuses on grid demand infrastructure to identify EV charger locations. Our study focuses on utilizing driver behavior (telematics) data that Min. the investment cost and Max. EV charger utility subjected to constraints that address budget and range anxiety of EV users
2. After the first step (DBSCAN), 90% of the identified clusters were at intuitively reasonable public locations but still contained noise like residential locations that are frequented by same vehicle.
3. In step-2 (optimization), we set the budget to select 15 locations and all identified clusters ***highlighted*** in ***fig(3)*** were at reasonable public locations where we have hospitals, movie theatres, Walmart, Kroger, Malls, etc. which are frequented often and for long periods of time thus, maximizing the utility of the charging station as well as improving the user experience of EV drivers