Placing Electric Vehicle Charging Stations: An Optimization Problem and Unsupervised Machine Learning Solution

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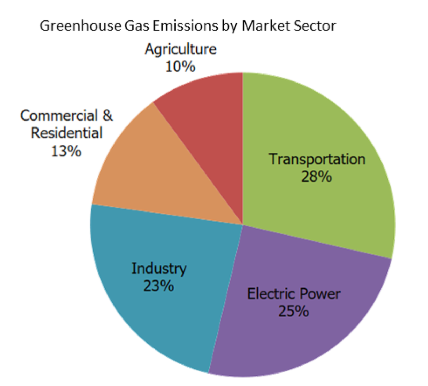
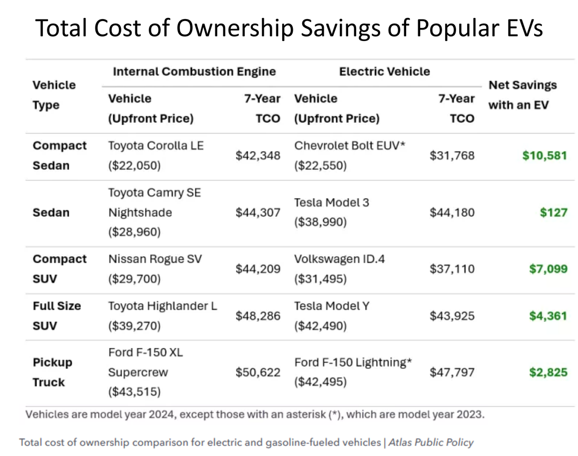
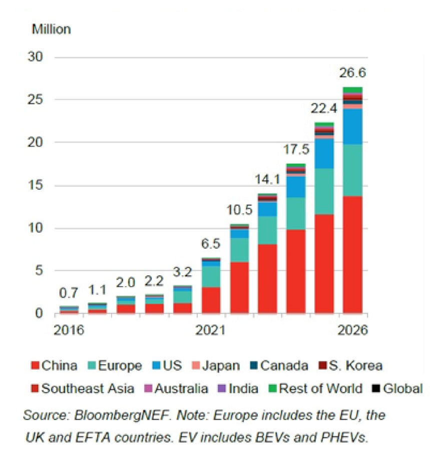
1. Introduction and Background

- Transportation is the single largest contributor to greenhouse emissions in the US
- Electric vehicles (EVs) offer a promising pathway to reducing transportation emissions and costs
- The projected rapid growth of EVs requires adequate charging infrastructure
  - "Range anxiety" is one of the major concerns cited by prospective buyers
  - US EV targets will require 1.2 million new public charging stations (20x the current number) by 2030
- Where should new charging stations be placed?
  - Currently, public EV charging stations are set up in an ad hoc market-driven manner

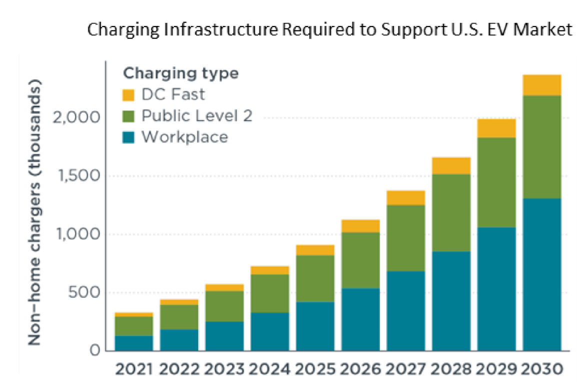


Source: US Environmental Protection Agency





Source: BloombergNEF



Source: International Council on Clean Transportation

2. Project Goals

- **Engineering Goal:** Develop algorithms and a software tool to determine optimal locations for EV charging stations
  - Can be used by government and industry to maximize impact of future investments
- What factors should we consider?
  - Convenience
  - Capacity
  - Coverage

Limitations of Prior Methods
- Single-objective
- Inflexible cost function
- Cannot apply hard constraints (e.g., no-go zones)

Convenience: Average distance between users and charging stations

Capacity: Number of users each station is expected to serve

Coverage: Maximum allowable distance from each user to the closest station

3. Optimization Problem Formulation

- Inputs
  - Geospatial data (EV density)
  - Locations of current charging stations
  - User-specified limits for capacity and coverage
  - Number of charging stations to place
- Outputs
  - Suggested locations for charging stations
  - Metrics
- Formulation

Objective:

$$\min_{s_j, c_{ij}} \frac{1}{\sum_i w_i} \sum_i \left(w_i \sum_j d(x_i, s_j)\, c_{ij}\right)$$

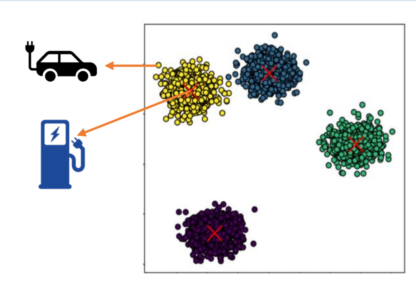
Constraints:
- $\sum_j c_{ij} = 1$
- $\sum_i w_i c_{ij} \le max\_capacity$
- $\sum_i d(x_i, s_j) \le max\_distance$

Variable	Definition
N	*Number of cells the target region is divided into*
K	*Number of charging stations*
x_i	*Location (latitude, longitude) of cell i (i = 1… N)*
s_j	*Location of station j (j = 1… K)*
w_i	*Count of electric vehicles in cell i*
$d(x_i, s_j)$	*Distance between x_i and s_j*
c_{ij}	*Assignment of cells to stations. $c_{ij} = 1$ iff. cell location i maps to station j; 0 otherwise*
max_capacity	*maximum number of users per station*
max_distance	*maximum allowable distance from a user to their closest station*

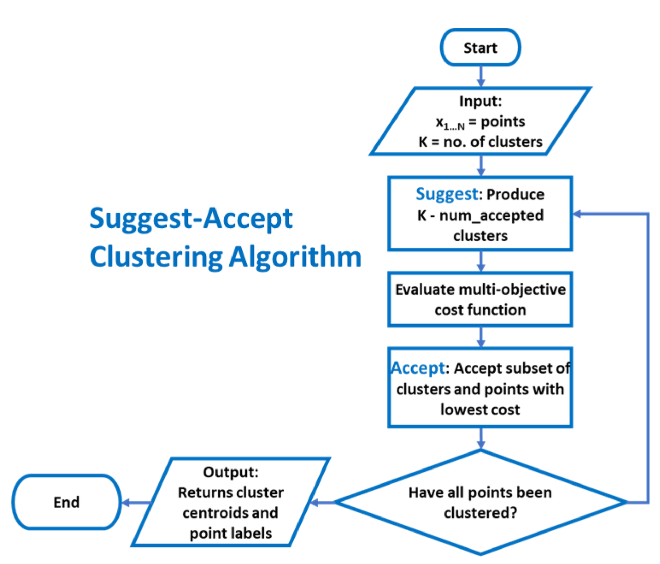
Brute-force solution requires $O(k^N)$ time
Even special cases of this problem have been shown to be NP-Hard (Mahajan et al., 2009)

4. Unsupervised Machine Learning Solution

- Clustering, an unsupervised machine learning technique, can be used to group similar or nearby points in a data set
- Naturally suited to EV station placement
  - EV locations → points, Stations → cluster centroids
- State-of-the-art clustering algorithms implemented in EV-Planner
  - K-means (Lloyd, 1982), Bisecting K-means (Steinback et al., 2000), Constrained K-means (Bradley et al., 2000)
  - **Limitation:** Cannot directly incorporate multi-objective cost function
- **Novel clustering algorithm:** Suggest-Accept Clustering
  - Iterative two-step method consisting of generation of clusters (any existing algorithm) followed by acceptance of clusters (flexible cost function and constraints)

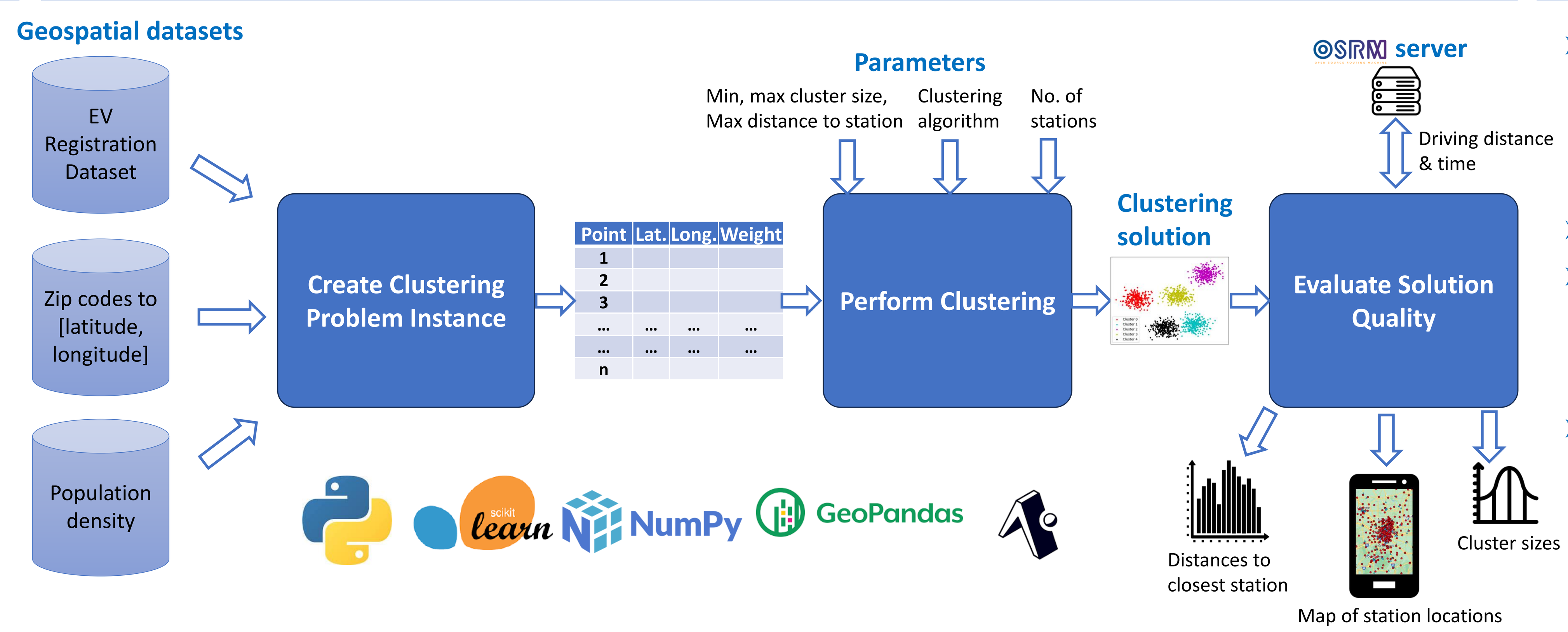


Suggest-Accept Clustering Algorithm



Algorithm	Average distance	Balanced Clusters	Ability to add constraints	Multi-objective Cost Function	Runtime
K-means	Lowest	Least	No	No	Low
Bisecting K-means	High	Moderate	No	No	Lowest
Constrained K-means	Highest	Moderate	Limited	No	High
Suggest-Accept Clustering (Proposed)	Low	Most	Yes	Yes	Low

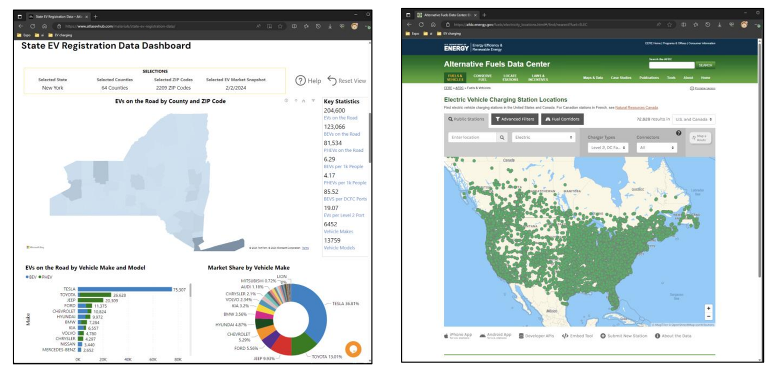
5. EV-Planner Software Architecture

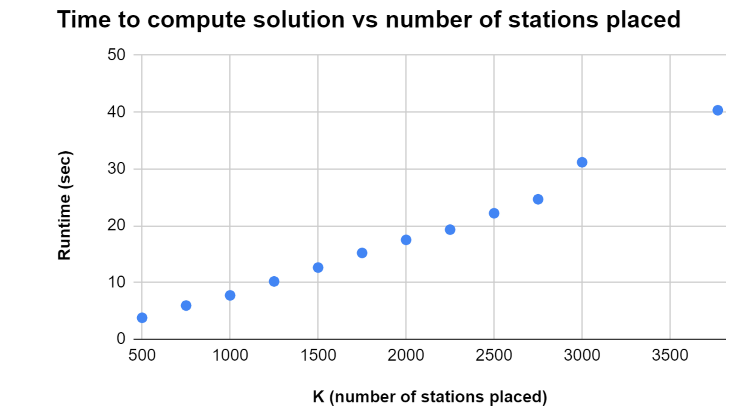


- EV-Planner was implemented in Python using the scikit-learn, numpy, pandas, and geopandas libraries
- Visualization app developed using Expo React Native framework

6. Experimental Setup

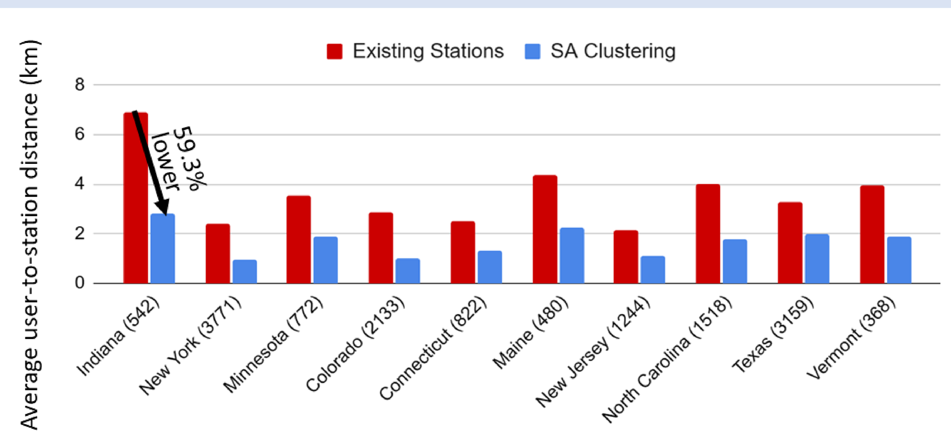
- Public datasets used
  - EV registrations (Atlas EV Hub)
  - Current charging stations (US DoE Alternative Fuels Data Center)
  - Population density (Kontur)
- Evaluated across 10 US states
- Experiments run on Lenovo Yoga 9 Laptop (Intel Core i7-1185G7 CPU, 16GB RAM) and Dell desktop (Intel Core i7-12700, 32GB RAM)
- Fast enough to be applied at the local, state and national scales
  - Placing 3771 stations for 171,000 EVs across the state of New York takes less than a minute
  - Runtime scales linearly with respect to number of charging stations (K) or number of EVs (N)

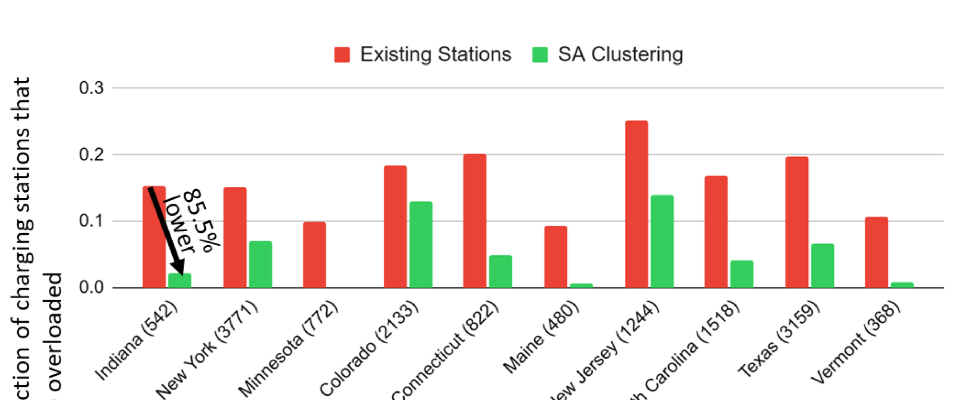




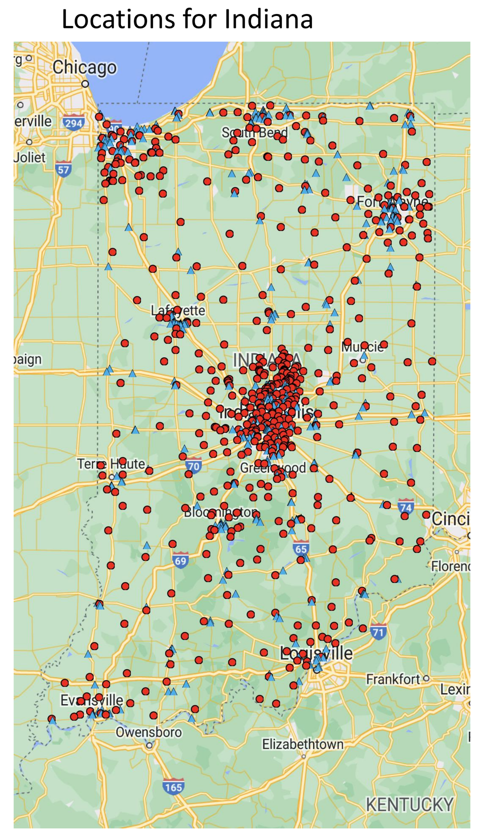
7. Experimental Results

- EV-Planner reduces average distances to charging stations by 52.3%
  - Saves 126 miles/user/year (106 million miles/year across all EVs in 10 states)
- EV-Planner reduces the number of overloaded EV charging stations by 71.7%
  - Improved load balance results in lower user wait times



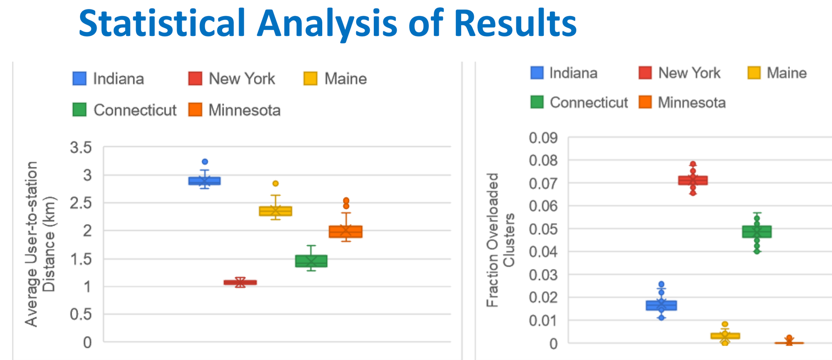


Suggested vs. Existing Station Locations for Indiana



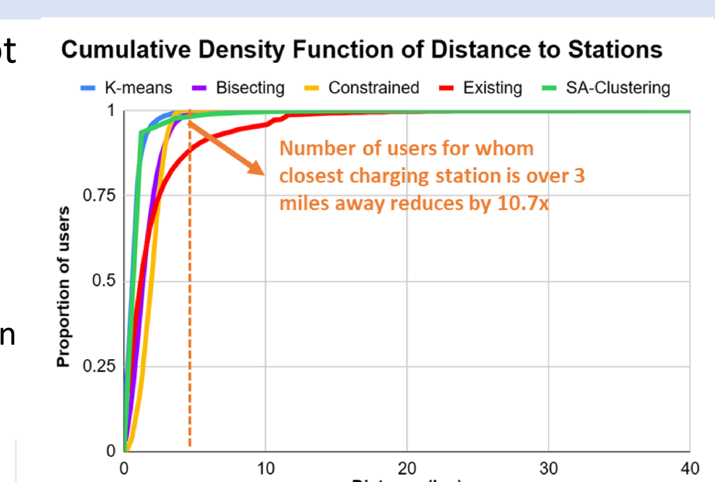
- EV-Planner reduces number of users who do not have access to a station within 3 miles by 10.7x
- SA Clustering outperforms current state-of-the-art algorithms (K-Means, Bisecting K-Means, Constrained K-Means)
  - Improvement due to the use of a separate accept step, which incorporates multi-objective cost function

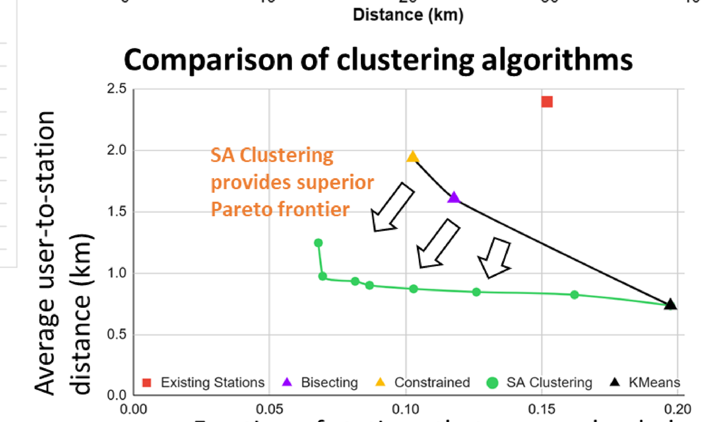
Statistical Analysis of Results



Confidence intervals (100 runs with varying random seeds) using Student's t-distribution

State	IN	NY	ME	CT	MN
99% Confidence Interval	2.892 ± 0.024	1.070 ± 0.010	2.362 ± 0.029	1.451 ± 0.031	2.012 ± 0.041





8. Conclusions

- Electric Vehicles offer a pathway to reducing transportation emissions and costs, but require significant growth in charging infrastructure
  - Public charging stations essential to ensuring broad and equitable adoption of EVs
- EV-Planner contributions
  - Multi-objective optimization problem formulation that considers user convenience, coverage and load balancing across stations
  - Novel unsupervised machine learning algorithm (SA Clustering)
- SA Clustering outperforms current state-of-the-art clustering algorithms
- EV-Planner can be used by government and industry to guide future deployment of public charging infrastructure
- Future work: Include other considerations such as proximity to retail locations, real estate costs, grid capacity, etc.

References

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