SMU/Bush Institute PostDoc

Bi-weekly progress report

Feb 28th, 2023

Literature review

Methodologies

- Statistical analysis
- Agent-based Modeling (ABM)

SystDynamics(SD)
em

- Machine Learning (ML)
- Integrating ML with ABM

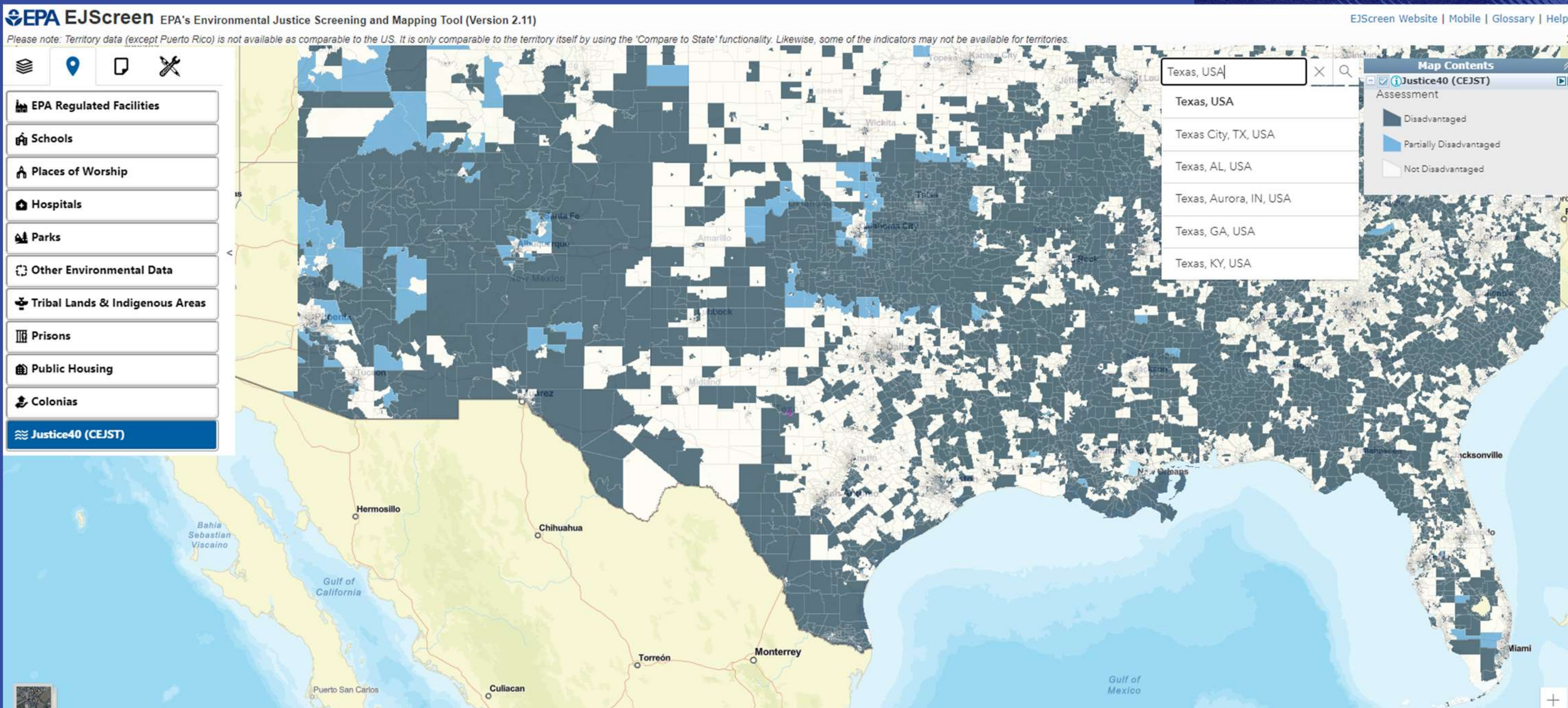
Topics

- Equity
- Low-income/disadvantaged communities
- Coupling EV stations with electric grid
- Policies: subsidies, rebates, grants, incentives, tax credits, etc.

Limitations

- Not that much data available at the time
- Research on NYC, LA, Chicago area, no Dallas/Texas
- Difficulty of validating ABM models
- Policy independence between Electricity and EV departments (e.g. independent incentive programs, rebates)

EPA EJ screen: Justice40 (CEJST)

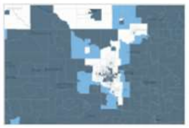


» https://ejscreen.epa.gov/mapper/

Justice40 Tracts

Justice40 Tracts November 2022 Version 1.0

Overview | Data | Visualization



This layer assesses and identifies communities that are disadvantaged according to updated Justice40 Initiative criteria in the U.S. and its territories. Census tracts that meet the Version 1.0 criteria are shaded in semi-transparent blue colors to work with a variety of basemaps.

Feature layer by esri_demographics

Item created: Nov 22, 2022 Item updated: Mar 5, 2023 View count: 74,512

Living Atlas

Open in Map Viewer

Open in Scene Viewer

Open in ArcGIS Desktop

Metadata

Description

This layer assesses and identifies communities that are disadvantaged according to updated Justice40 Initiative criteria. Census tracts in the U.S. and its territories that meet the Version 1.0 criteria are shaded in semi-transparent blue colors to work with a variety of basemaps. See this web map for use in your dashboards, story maps, and apps.

Details of the assessment are provided in the popup for every census tract in the United States and its territories American Samoa, Guam, the Northern Mariana Islands, Puerto Rico, and the U.S. Virgin Islands. This map uses 2010 census tracts from Version 1.0 of the source data downloaded November 22, 2022.

If you have been using a previous version of the Justice40 data, please know that this Version 1.0 differs in many ways. See the updated Justice40 Initiative criteria for current specifics.

Use this layer to help plan for grant applications, to perform spatial analysis, and to create informative dashboards and web applications. See this blog post for more information.

From the source:

This data "highlights disadvantaged census tracts across all 50 states, the District of Columbia, and the U.S. territories. Communities are considered disadvantaged:

- *If they are in census tracts that meet the thresholds for at least one of the tool's categories of burden, or*
- *If they are on land within the boundaries of Federally Recognized Tribes*

Categories of Burdens

The tool uses datasets as indicators of burdens. The burdens are organized into categories. A community is highlighted as disadvantaged on the CEJST map if it is in a census tract that is (1) at or above the threshold for one or more environmental, climate, or other burdens, and (2) at or above the threshold for an associated socioeconomic burden.

In addition, a census tract that is completely surrounded by disadvantaged communities and is at or above the 50% percentile for low income is also considered disadvantaged.

Details

Source: Feature Service
Data updated: Mar 5, 2023, 11:37 PM
Schema updated: Apr 5, 2023, 3:31 PM
Size: 1,804.938 MB
Attachments size: 0 KB
ID: f95344889cab44bd84207052f44cb940

Share

Owner

esri_demographics

Tags

social, equity, ACS, American Community Survey, FEMA, National Risk Index, NRI, Energy, LEAD, EPA, EJSCREEN, Office of Air and Radiation, OAR, EPA National Air Toxics Assessment, NATA, Department of Transportation, DOT, Comprehensive Housing Affordability Strategy, CHAS, RCRA, CERCLIS, RMP Risk-Screening

From the source:
This data "highlights disadvantaged census tracts across all 50 states, the District of Columbia, and the U.S. territories.
Communities are considered disadvantaged:
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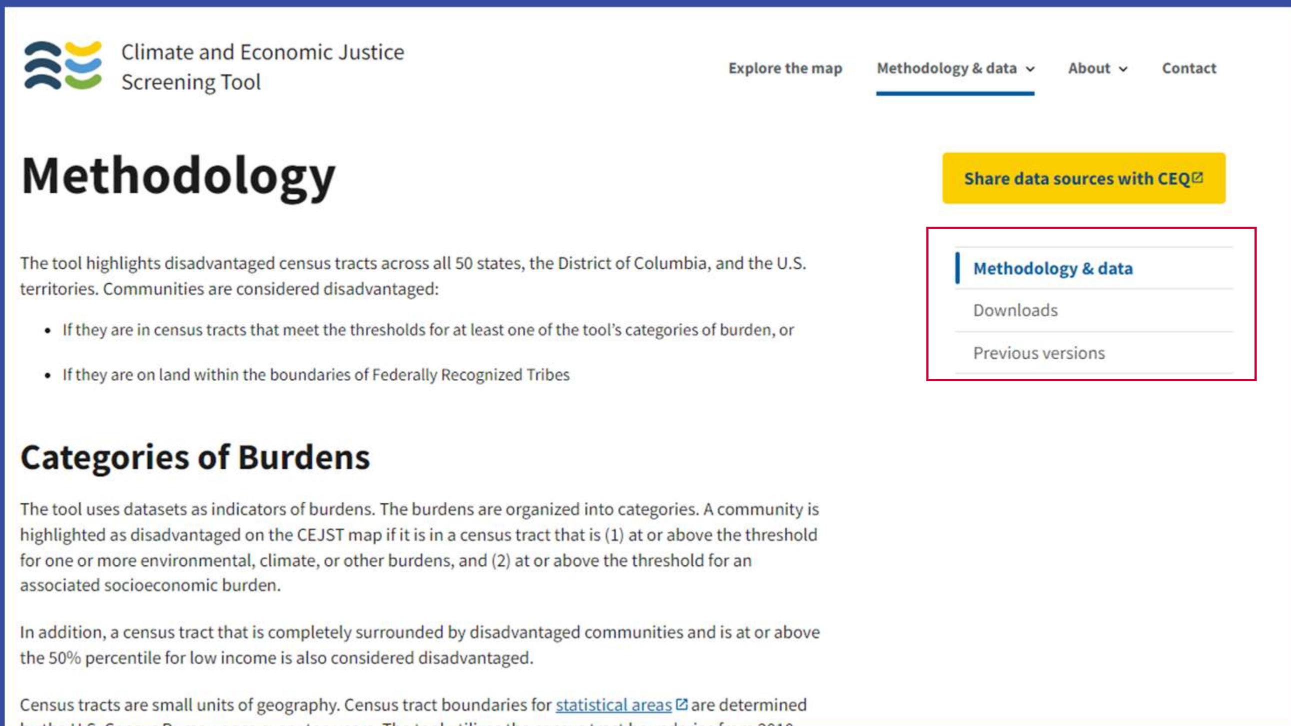
•If they are on land within the boundaries of Federally Recognized Tribes

Justice40 Initiative criteria

arcgis-blog

SMU®

https://www.arcgis.com/home/item.html?id=f95344889cab44bd84207052f44cb940



Climate and Economic Justice Screening Tool

Explore the map | Methodology & data | About | Contact

Methodology

Share data sources with CEQ

- Methodology & data
- Downloads
- Previous versions

The tool highlights disadvantaged census tracts across all 50 states, the District of Columbia, and the U.S. territories. Communities are considered disadvantaged:

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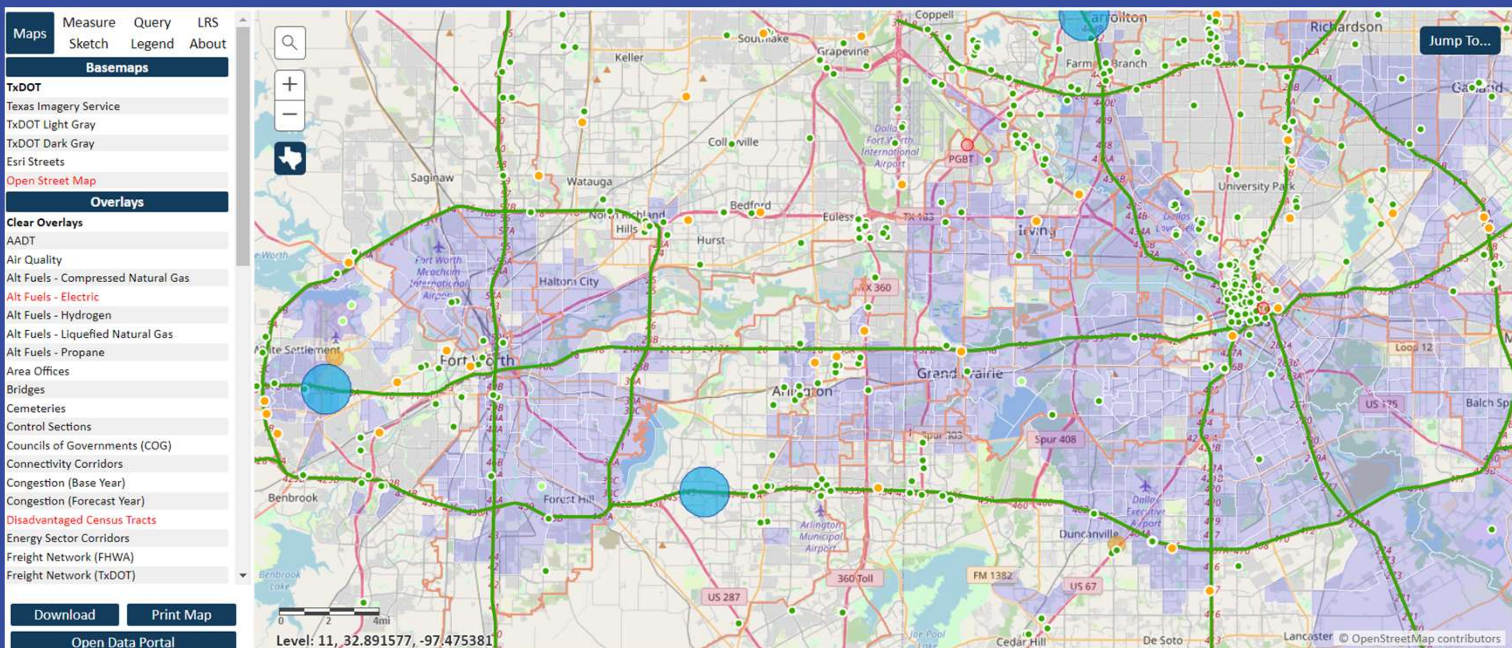
In addition, a census tract that is completely surrounded by disadvantaged communities and is at or above the 50% percentile for low income is also considered disadvantaged.

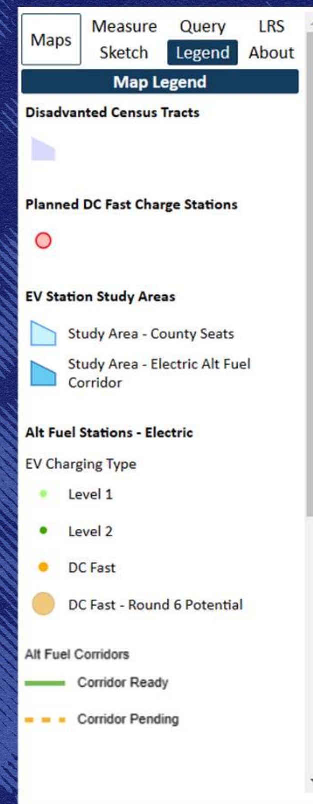
Census tracts are small units of geography. Census tract boundaries for statistical areas are determined by the U.S. Census Bureau once every ten years. The tool utilizes the census tract boundaries from 2010

https://screeningtool.geoplatform.gov/en/methodology

Dataset: o_TXDoT\texas EV stations

EV charging stations and underserved communities mapping





[Statewide Planning Map (txdot.gov)]

Dataset: 1_DoE\Alternative Fuel Data Center(AFDC)

EV charging stations data:

Fuel Type	Station Na	Street Add	Intersectic	City	State	ZIP	Plus4	Station Ph	Status Cod	Expected D	Groups Wi	Access Day	Cards Acce	BD Blends	NG Fill Typ	NG PSI	EV Level1	EV Level2	EV DC Fast	EV Other I	EV Networ	EV N
ELEC	LADWP - T	11797 Truesdale St		Sun Valley	CA	91352			E		Private	Fleet use only						39	3		Non-Networke	
ELEC	LADWP - V	1394 S Sepulveda Blvd		Los Angele	CA	90024			E		Private							4			Non-Networke	

Policies: Laws and incentives

Law Id	State	Title	Text	Enacted D	Amended I	Recent?	Sequence	Type	Agency	Significant	Expired Da	Archived D	Repealed I	Topic	Technolog	Incentive	Regulation	User Categ	Referen
4739	TX	Propane a	The			FALSE	135	Laws and Regulations		2018-09-10 14:12:22 UTC					NG|LPG		OTHER	STATION|/	http://w
5309	TX	Clean Vehi	The Texas			FALSE	25	State Incentives		2018-06-18 15:30:15 UTC					AFTMKTC(	GNT		STATION|I	http://w
5312	TX	Natural Ga	The Texas			FALSE	80	Utility/Private Incenti		2015-08-11 15:37:53 UTC					AFTMKTC(	RBATE		MAN|FLEET|IND	

Vehicle info: light/medium/heavy duty

Vehicle ID	Fuel ID	Fuel Confi	Manufactu	Category I	Model	Model Yea	Alternative	Alternative	Alternative	Conventio	Conventio	Conventio	Transmissi	Engine Typ	Engine Size	Engine Cyl	Engine/Mc	Manufactu	Manufactu	Category	Fuel Code	Fuel
13140	45	9	377	27	A3	2023				28	38	32	Auto	SI	2.0L	4	2.0L I4	Audi	http://pro	Sedan/Wa	HYBR	Hybrid Ele
13139	45	9	377	27	A3 quattro	2023				27	35	30	Auto	SI	2.0L	4	2.0L I4	Audi	http://pro	Sedan/Wa	HYBR	Hybrid Ele
13141	45	9	377	27	A4 quattro	2023						26-28	Auto	SI	2.0L	4	2.0L I4	Audi	http://pro	Sedan/Wa	HYBR	Hybrid Ele

[Map with API access](#)
[Alternative Fuels Data Center: Electric Vehicle Charging Station Locations (energy.gov)](#)

[Alternative Fuels Data Center: Data Downloads (energy.gov)](#)

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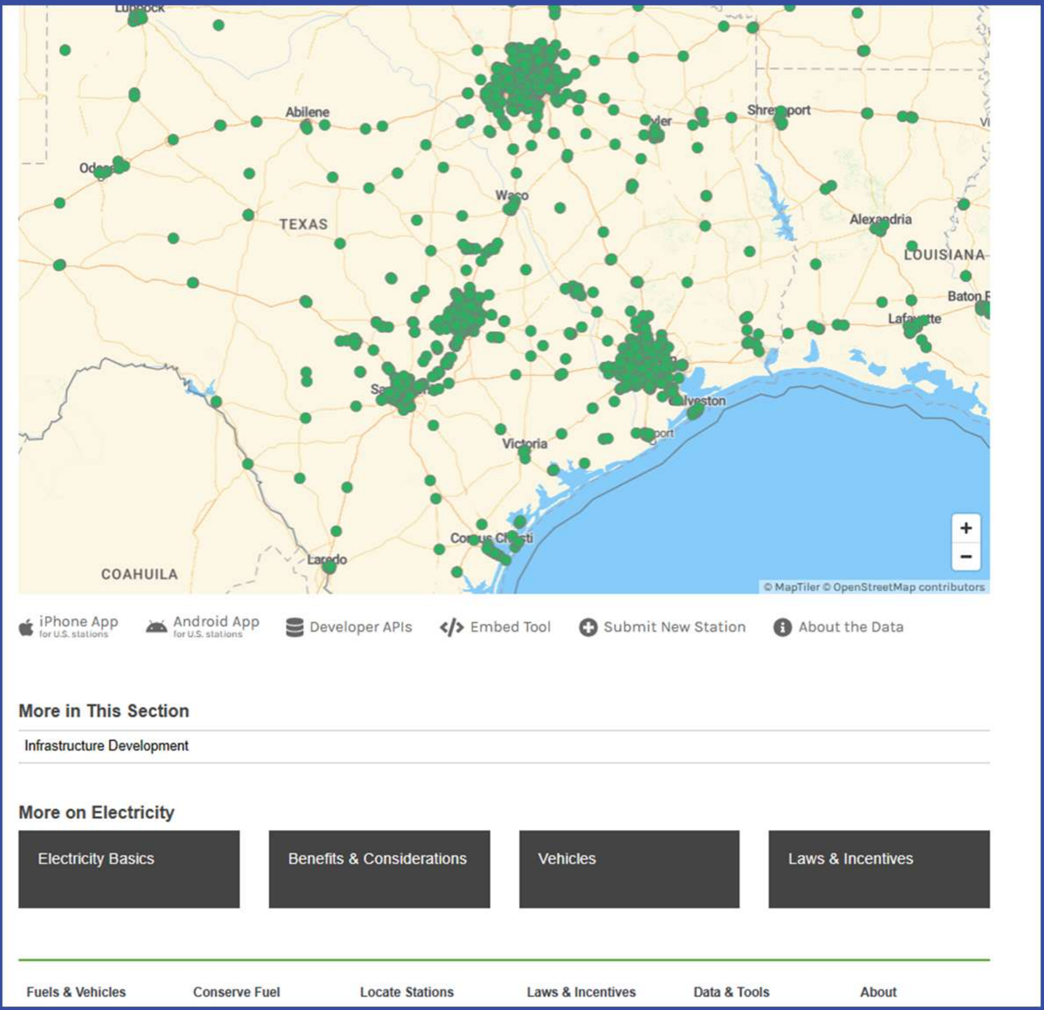
Dataset: 1_DoE\Alternative Fuel Data Center(AFDC)



[Alternative Fuels Data Center: Tools (energy.gov)]

[Alternative Fuels Data Center: Data Downloads (energy.gov)]

[Alternative Fuel Stations API | NREL: Developer Network]

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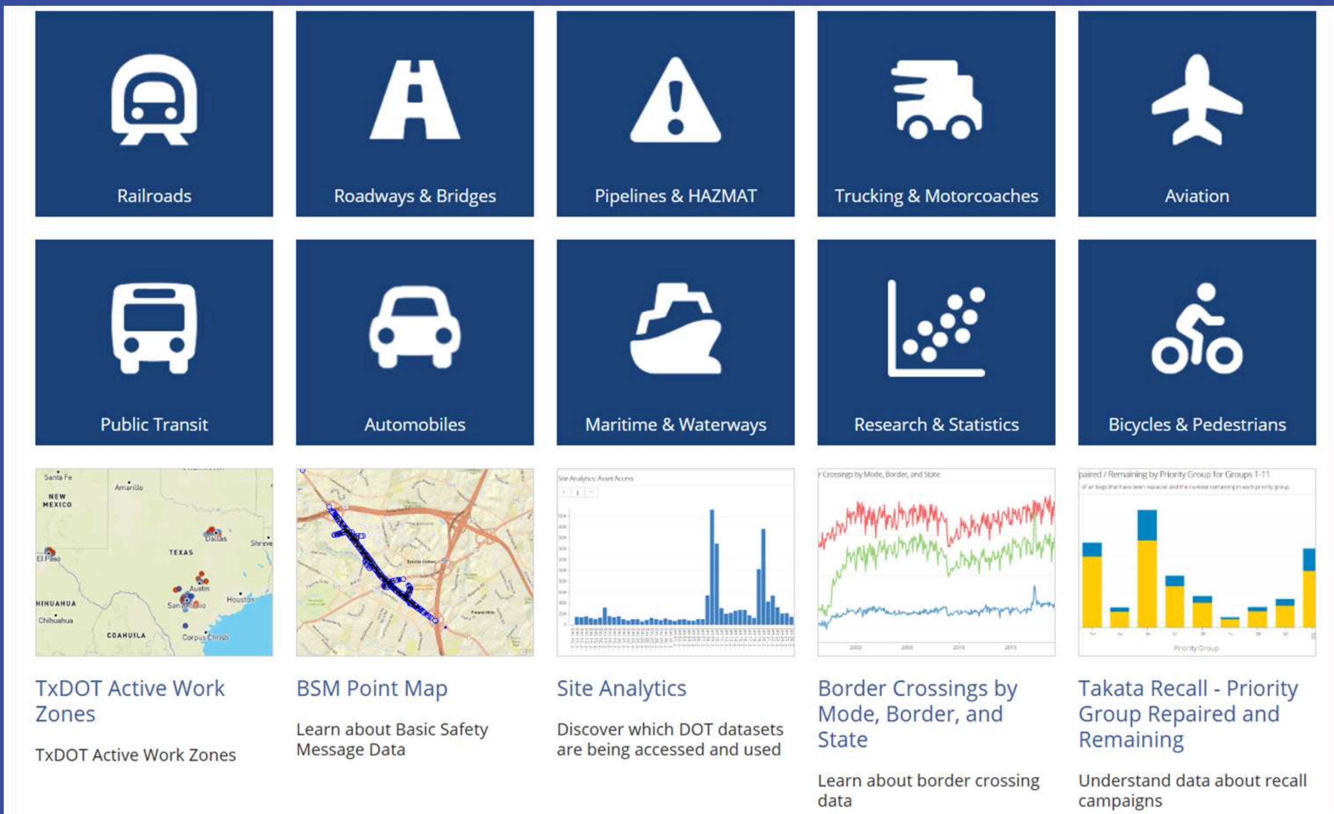
Dataset:6_BureauTransportationStatistics



[Department of Transportation - Open Data Portal |](#)

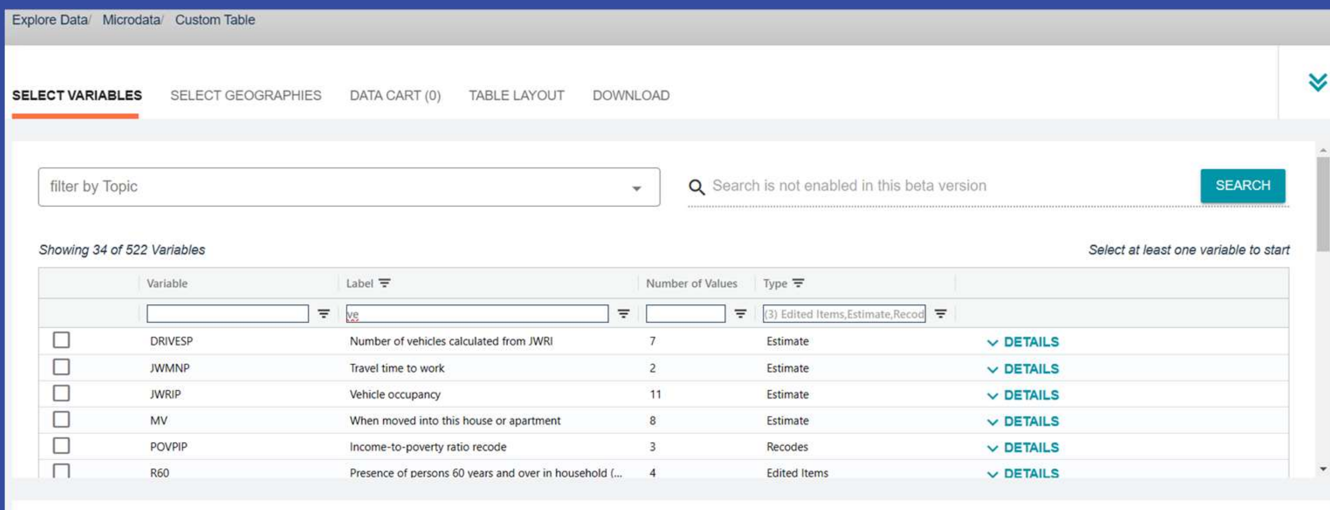
[Video Guides | Department of Transportation - Data Portal](#)

[Socrata Developers | Socrata](#)

Dataset: 2.U.S. Census Bureau

Public Use Microdata Sample:
This contains lots of **demographic data**, including race, gender, age, household income, employment, commute time, vehicle occupancy, etc.

Custom demographic data tables available but limited to maximum number of variables and its layouts. Need to figure out an approach to retrieve the data programmatically and store it in an organized database for future use.



- American Community Survey (ACS): ACS 1-Year, ACS Migration Flows
- Economic Indicators Time Series
- Decennial Census
- Economic Census
- County Business Patterns and Nonemployer Statistics
- Population Estimates and Projections
- International Trade

[Datasets (census.gov)](#)

[Census Bureau Data](#)

[Available APIs (census.gov)](#)

[**MDAT (census.gov)**](#)

[Census Microdata API](#)

[Census Academy](#)

[Economic Census](#)

[Data Science & Visualization Resources (census.gov)](#)

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Dataset: 2.U.S. Census Bureau-API

local file: Census Data API User guide

Census Data API: /data

Dataset:5_US Bureau of Labor Statistics

Inflation & Prices >>

- Consumer Price Index
- Producer Price Indexes
- Import/Export Price Indexes
- Contract Escalation
- Price Index Research

Pay & Benefits >>

- Employment Costs
- Wage Data by Occupation
- Earnings by Demographics
- Earnings by Industry
- County Wages
- Benefits
- Modeled Wage Estimates
- Compensation Research
- Strikes & Lockouts

Occupational Requirements >>

Unemployment >>

- National Unemployment Rate
- State & Local Unemployment Rates
- Unemployment Research

Employment >>

- National Employment
- State & Local Employment
- County Employment
- Worker Characteristics
- American Indian Report
- Employment Projections
- Job Openings & Labor Turnover Survey
- Business Response Survey
- Employment by Occupation
- Work Experience Over Time
- Business Employment Dynamics
- Foreign Direct Investment
- Employment Research

Workplace Injuries >>

Productivity >>

- Labor and Total Factor Productivity
- Productivity Research

Spending & Time Use >>

- Consumer Expenditures
- How Americans Spend Time

International >>

- International Technical Cooperation
- Import/Export Price Indexes

Geographic Information >>

- New England (Boston)
- New York-New Jersey (NY City)
- Mid-Atlantic (Philadelphia)
- Southeast (Atlanta)
- Midwest (Chicago)
- Southwest (Dallas)
- Mountain-Plains (Kansas City)
- West (San Francisco)

Accessing the Public Data API with R : U.S. Bureau of Labor Statistics (bls.gov)

How many electric vehicle charging stations are there in the US? - USAFacts

How do tax credits for electric cars work? - USAFacts

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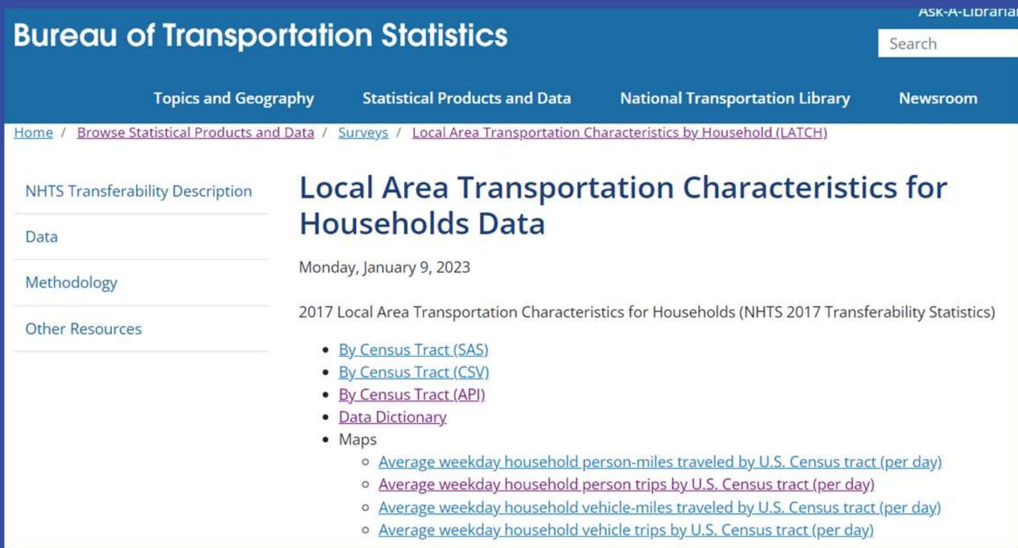
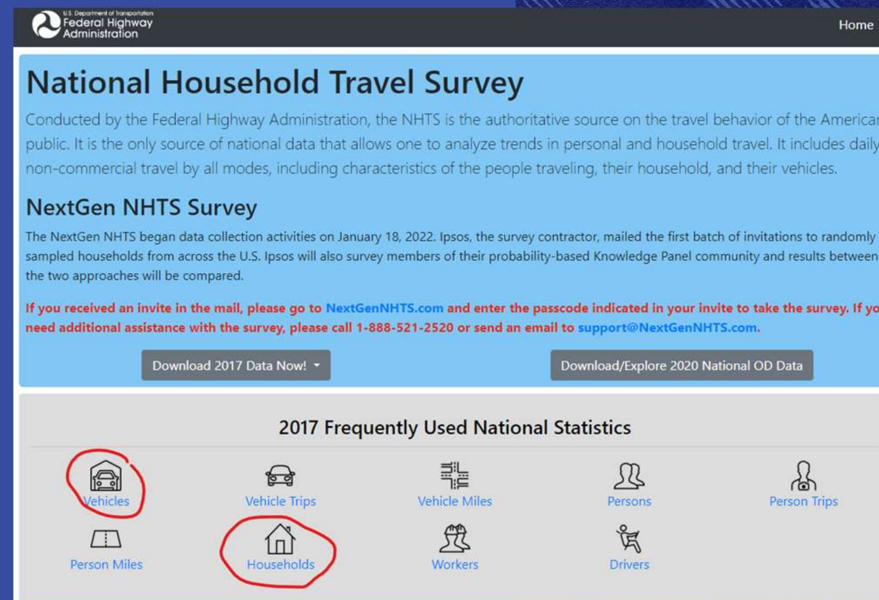
Dataset:6-1_National Household Travel Survey





https://www.bts.gov/latch/latch-data

https://www.bts.gov/browse-statistical-products-and-data

https://nhts.ornl.gov/

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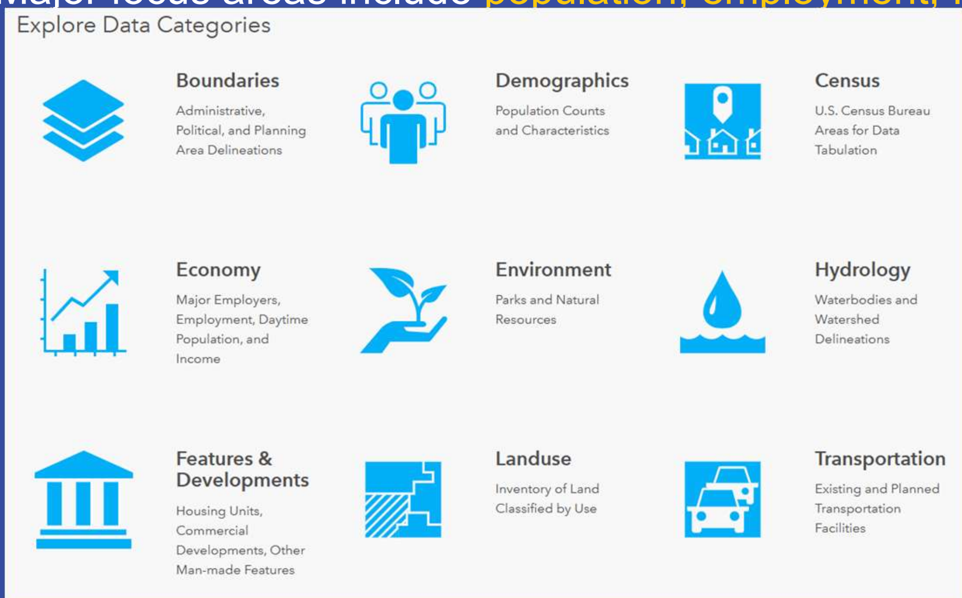
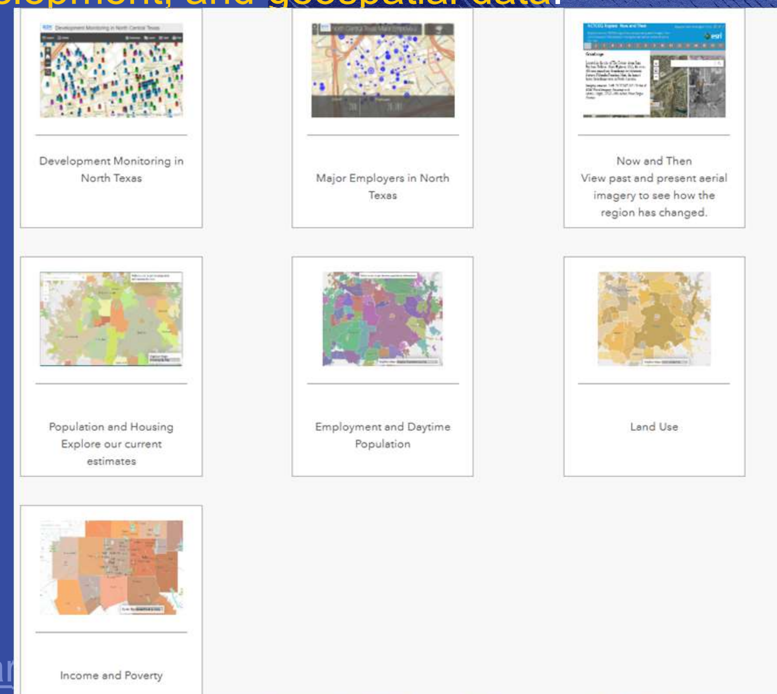
2021 Vehicle Inventory and Use Survey (VIUS) Available Fall 2023

Dataset: 3_NorthCentralTexasCouncilGov

» The Regional Data Center

» is a service of the Research and Information Services (RIS) department. RIS provides objective information and analysis on the development of the region for use in planning and economic development activities. Major focus areas include population, employment, land use, development, and geospatial data.



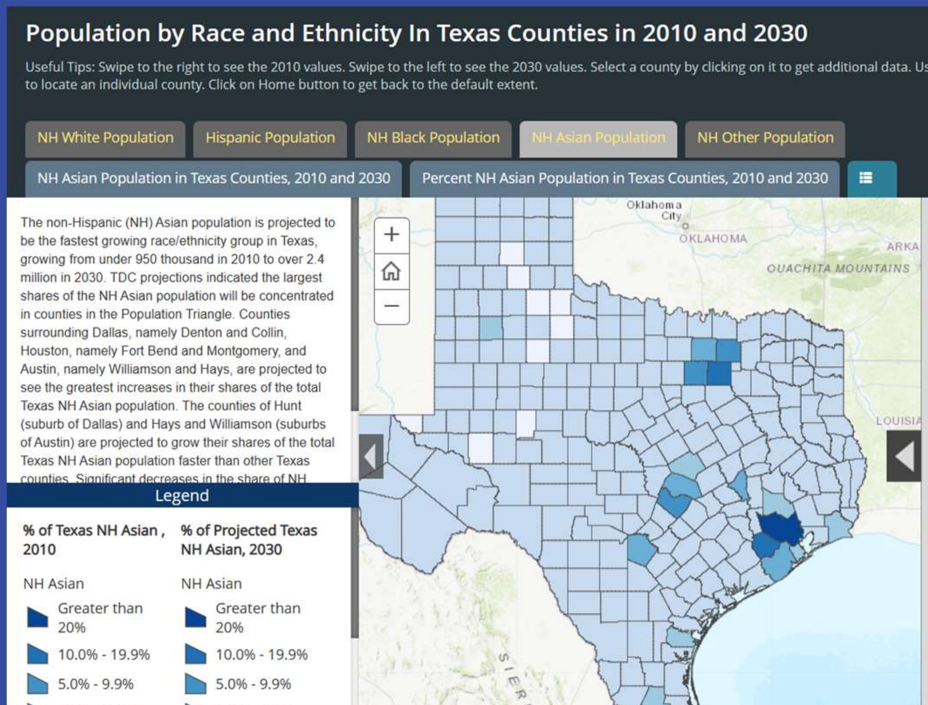


Regional Data Center - North Central Texas Council of Governments (ar

Search for '*' | North Central Texas Council of Governments (arcgis.com)

2045 NCTCOG Demographic Forecast (City) | 2045 NCTCOG Demographic Forecast (City) | North Central Texas Council of Governments (arcgis.com)

Dataset:4_Texas demographic center



[Texas Demographic Center]

[Population by Race and Ethnicity In Texas Counties in 2010 and 2030 (arcgis.com)]

[Population Projections for Texas Counties, 2020-2040 and 2020-2060 (arcgis.com)]

NREL

Developer Network

HOME | DOCUMENTATION | COMMUNITY

Documentation » Electricity

Electricity

Services associated with electricity costs, generation, transmission, delivery, and m

OpenEI Utility Rates

Access complex utility rate structure information (across all sectors) for most U.S. utility companies from the National Utility Rate Database. This information is collected and quality controlled on a continual basis by Illinois State University on behalf of DOE and housed within the OpenEI.org platform.

Utility Rates (GET /api/utility_rates/v3)

This service returns annual average utility rates ($/kWH) for residential, commercial and industrial sectors as well as the local utility name for a specific location. This service does not return complex rate information.

Utility Rates by Census Region (GET /api/census_rate/v3)

Given a location and Census Bureau region level (block, blockgroup, tract), return the Census Bureau ID, utility rate and company information.

Deprecated

Energy Incentives (Version 2 - Deprecated) (/api/energy_incentives/v2/dsire)

Deprecated: This service lists the incentives found in the DSIRE database by location.

Web Services

Available Web Services

- REST - provides a RESTful wrapper around high-value data.
  - Term extraction
    - Documentation
    - includes content recommendation engine
  - Utility Companies
    - Documentation Version 2, Version 3
    - Human-readable source data
    - Also see: the utilities gateway
  - Utility Rates
    - International Utility Rate Database API Documentation
    - U.S. Utility Rate Database API Documentation
    - Also see: the Utilities Gateway
  - Incentives for Renewables & Efficiency
    - Documentation
    - Also see: the incentives & policies gateway
- Ask queries
  - inline queries for Semantic MediaWiki
- SPARQL queries
- NREL's developer network
- Hackathon Resources

Developer Network

HOME | DOCUMENTATION | COMMUNITY

The National Renewable Energy Laboratory's devel
energy and alternative fuel data.

Web Service Documentation ▸

Explore our available Web services.

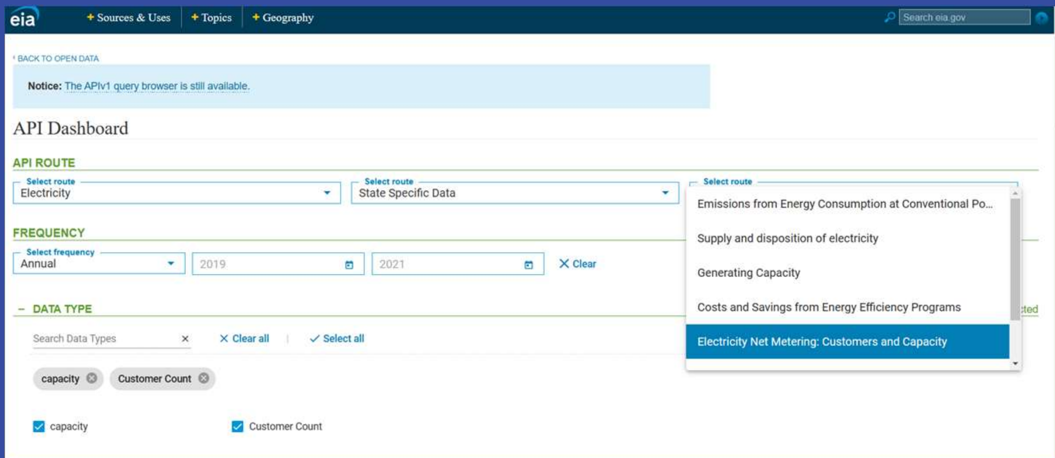
- Buildings
- Electricity
- Energy Optimization
- Partnering
- Solar
- Transportation
- Wave
- Wind

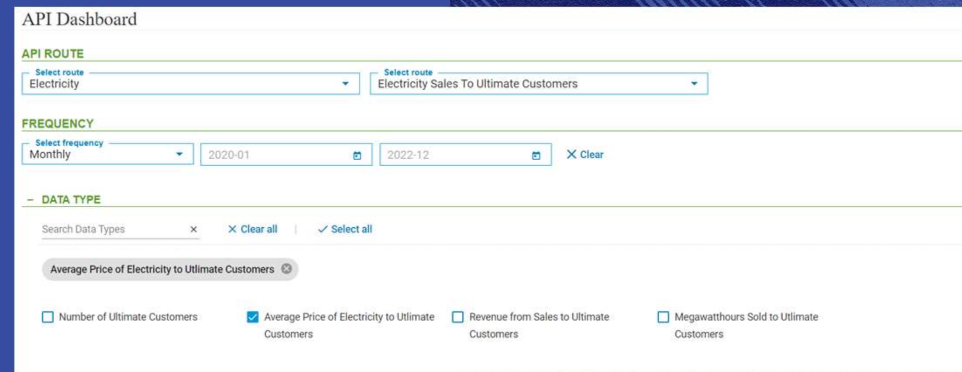
BCL (nrel.gov)

Electricity APIs | NREL: Developer Network

NREL: Developer Network

Dataset:7_USEIA





[API Dashboard - U.S. Energy Information Administration (EIA)]

[API Dashboard - U.S. Energy Information Administration (EIA)]

[Opendata - U.S. Energy Information Administration (EIA)]

SMU

Dataset:8_OEDI

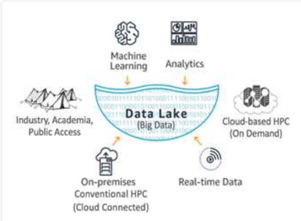
Open Energy Data Initiative

Universal Accessibility

Our open architecture is designed for universal access and dissemination of big data. Data Lakes can be accessed via our cloud partners. There are a few ways to utilize Data Lakes. Jupyter notebooks are a common option for utilizing Data Lakes datasets. However, there are many options for processing Data Lakes.

Multiple Ways to Access

- Jupyter notebooks (example)
- Google Earth Engine
- Direct access to Data Lakes (Requires a cloud account.)
- Data Lake Viewer (Currently only AWS)
- Native cloud command line tools (AWS, Google, Azure)
- Mounting the data as a local read-only drive in a cloud-built computer cluster. Requires same availability zone.



Data stored in the lake is actionable and discoverable, increasing accessibility to large and complex datasets.

Manual Download and AWS CLI

- Download datasets via data-catalog viewer, users may process data in ways they see fit. Alternatively, batch download via Amazon's Command Line Interface.
- **Free** for end users.
- Learn More.

S3 Tools and APIs

- Access data with S3 Tools and APIs to analyze datasets.
- **Free** for end users.
- Learn More.

Google BigQuery

- Google BigQuery is a serverless, highly scalable data warehouse that comes with Google's built-in query engine.
- BigQuery offers two pricing models (On-demand and Flat-rate pricing) for running queries, **often less than $0.10**
- Learn More.

AWS SageMaker Studio

- The SageMaker Studio provides a web-based integrated development environment (IDE) where users can see and interact with all ML workflows on AWS.
- **End user costs are often less than $20.** Use Amazon SageMaker Savings Plan to reduce costs by up to 64%, compared to On-Demand pricing.
- Learn More.

HSDS and Jupyter Notebook

- Highly Scalable Data Service (HSDS) is a REST-based product and solution for reading and writing complex binary data formats within an object-based storage environment, such as the Cloud.
- **Free** for end users.
- Learn More.

AWS Athena

- Athena is an interactive query service offered by AWS that makes it easy to access data in Amazon S3 using SQL.
- AWS Athena can be used for a small fee, **often less than $1.**
- Learn More.

Cloud-based HPC Cluster

-HPC (High Performance Computing) instances are ideal for applications that benefit from high-performance processors, such as large simulations and machine learning workloads.
- Multiple pricing models, **often less than $10.**
- Learn More.

AWS SageMaker Studio Lab

- Amazon SageMaker Studio Lab is a free machine learning (ML) development environment that provides the compute, storage (up to 15GB) and security to learn and experiment with ML.
- **Free** for end users.
- Learn More.

OEDI: All Data (openei.org)

https://data.openei.org/submissions/all

End-Use Load Profiles for the U.S. Building Stock

DOI 10.25984/1876417 Publicly accessible License

The United States is embarking on an ambitious transition to a 100% clean energy economy by 2050, which will require improving the flexibility of electric grids. One way to achieve grid flexibility is to shed or shift demand to align with changing grid needs. To facilitate this, it is critical to understand how and when energy is used. High quality end-use load profiles (EULPs) provide this information, and can help cities, states, and utilities understand the time-sensitive value of energy efficiency, demand response, and distributed energy resources. Publicly available EULPs have traditionally had limited application because of age and incomplete geographic representation. To help fill this gap, the U.S. Department of Energy (DOE) funded a three-year project, End-Use Load Profiles for the U.S. Building Stock, that culminated in this publicly available dataset of calibrated and validated 15-minute resolution load profiles for all major residential and commercial building types and end uses, across all climate regions in the United States. These EULF were created by calibrating the ResStock and ComStock physics-based building stock models using many different measured datasets, as described in the "Technical Report Documenting Methodology" linked in the submission.

Aggregate and Individual Building Timeseries End Use Load Profiles — View Data Lake 39.68 TB
Aggregate and individual building timeseries end use load profiles. See README.md file inside the dataset for data hierarchy, organization, etc.
8,896,627*

FAQ for End-Use Load Profiles Dataset — View
Answers to frequently asked questions about the End-Use Load Profiles dataset and ComStock/ResStock data viewers.

README — View Data Lake 39.68 TB
This file describes the organization of the datasets.
8,896,470*

Technical Report Documenting Methodology — View

OEDI: End-Use Load Profiles for the U.S. Building Stock (openei.org)

City and County Vehicle Inventories

DOI 10.25984/1788088 Publicly accessible License

This light-duty vehicle inventory dataset provides information on vehicle registrations by vehicle type (car vs. truck), fuel type, and model year showing the changes in adoption trends over time and average fuel economies.

This data is part of a suite of state and local energy profile data available at the "State and Local Energy Profile Data Suite" link below and builds on Cities-LEAP energy modeling, available at the "EERE Cities-LEAP Page" link below. Examples of how to use the data to inform energy planning can be found at the "Example Uses" link below.

City and County Vehicle Inventories.xlsb — Download 59.71 MB
The light-duty vehicle inventory dataset. Includes city and county vehicle data. This data includes vehicle type, fuel type, vehicle model year, and vehicle adoption.
1,238*

OEDI: City and County Vehicle Inventories (openei.org)

Sample IEEE123 Bus system for OEDI SI

Publicly accessible License

The aim of this project is to create an easy-to-use platform where various types of analytics can be performed on a wide range of electrical grid datasets. The aim is to establish an open-source library of algorithms that universities, national labs and other developers can contribute to which can be used on both open-source and proprietary grid data to improve the analysis of electrical distribution systems for the grid modeling community. OEDI Systems Integration (SI) is a grid algorithms and data analytics API created to standardize how data is sent between different modules that are run as part of a co-simulation.

This submission includes an IEEE123 bus system with time series load and PV data attached. An example electrical system, named the OEDI SI feeder, is used to test the workflow in the co-simulation. The system used is the IEEE123 test system, which is a well studied test system (see link below to IEEE PES Test Feeder), but some modifications were made to it to add some solar power modules and measurements on the system.

The readme file included in the S3 bucket provides information about the directory structure and how to use the algorithms. The sensors.json file is used to define the measurement locations.

Github OEDI SI IEEE123 Bus Test System — View Repository
Github link for the location of the IEEE123 bus system for testing the OEDI SI framework.

OEDI: Sample IEEE123 Bus system for OEDI SI (openei.org)

SMU

Dataset: 9_ercot

Electric Reliability Council of Texas

conditions.

View dashboards

+ Day-Ahead and Real-Time Displays

+ Real-Time Prices Reports

+ DAM Results Reports

+ System Conditions

+ Ancillary Service Plans

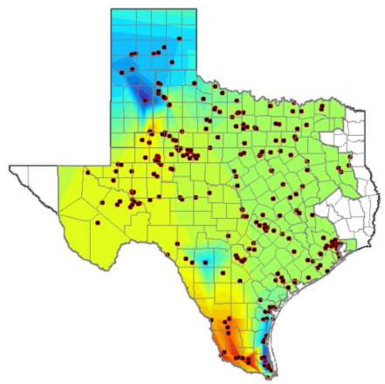
+ Scarcity Pricing Mechanism

real-time data

[Market Information (ercot.com)]

Real-Time Locational Prices

Updates every 5 minutes



[Grid and Market Conditions (ercot.com)]

https://www.ercot.com/gridmktinfo/dashboards

LMPs by Resource Nodes, Load Zones and Trading Hubs

The Locational Marginal Price for each Settlement Point, normally produced by SCED every five minutes.

+ Show EMIL Information

Friendly Name	Posted		Available Files
LMPSROSNODENP6788_20230301_161017_csv	3/1/2023	4:10:24 PM	zip
LMPSROSNODENP6788_20230301_161017_xml	3/1/2023	4:10:24 PM	zip
LMPSROSNODENP6788_20230301_160519_csv	3/1/2023	4:05:28 PM	zip
LMPSROSNODENP6788_20230301_160519_xml	3/1/2023	4:05:27 PM	zip
LMPSROSNODENP6788_20230301_160023_csv	3/1/2023	4:00:30 PM	zip
LMPSROSNODENP6788_20230301_160023_xml	3/1/2023	4:00:30 PM	zip
LMPSROSNODENP6788_20230301_155517_csv	3/1/2023	3:55:22 PM	zip

Home > Market Participants > EMIL > Data Product Details

LMPs by Electrical Bus

The Locational Marginal Price for each Electrical Bus, normally produced by SCED every five minutes.

+ Show EMIL Information

Friendly Name	Posted		Available Files
LMPSELECTBUSNP6787_20230301_161017_csv	3/1/2023	4:10:22 PM	zip
LMPSELECTBUSNP6787_20230301_161017_xml	3/1/2023	4:10:22 PM	zip
LMPSELECTBUSNP6787_20230301_160519_csv	3/1/2023	4:05:27 PM	zip
LMPSELECTBUSNP6787_20230301_160519_xml	3/1/2023	4:05:27 PM	zip
LMPSELECTBUSNP6787_20230301_160023_csv	3/1/2023	4:00:31 PM	zip

[Data Product Details (ercot.com)]

Assessment of Chronic Congestion

ERCOT, shall monitor the differences in Locational Marginal Prices from the Security-Constrained Economic Dispatch process to identify geographic areas potentially experiencing chronic congestion. Post all the results from this process on the MIS Secure Area and provide them to the PUCT Staff, the Independent Market Monitor (IMM), the appropriate ERCOT subcommittee(s), and the ERCOT Board of Directors.

Search for Related Topic(s): Congestion | Locational Marginal Price(LMP)

DAM Hourly LMPs

The Hourly Locational Marginal Prices per electrical bus from the Day-Ahead Market for the last thirty days on a daily basis.

Search for Related Topic(s): Day-Ahead Market(DAM) | Locational Marginal Price(LMP) | Market Results

LMPs by Electrical Bus

The Locational Marginal Price for each Electrical Bus, normally produced by SCED every five minutes.

Search for Related Topic(s): Security-Constrained Economic Dispatch(SCED) | Locational Marginal Price(LMP) | Disclosure Reports

LMPs by Resource Nodes, Load Zones and Trading Hubs

The Locational Marginal Price for each Settlement Point, normally produced by SCED every five minutes.

Search for Related Topic(s): Security-Constrained Economic Dispatch(SCED) | Locational Marginal Price(LMP) | Disclosure Reports

Notification of RTM Prices Under Investigation

ERCOT shall monitor Real-Time Locational Marginal Prices (LMPs), Supplemental Ancillary Services Market (SASM), Market Clearing Prices for Capacity (MCPCs), and Real-Time Settlement Point Prices for

Real-Time LMPs for Latest SCED Run Display

A display of the latest SCED Locational Marginal Prices (LMPs) by Resource Node settlement po latest on-line (RTORPA) and off-line (RTOFFPA) Real-Time Reserve Price Adder and the latest Rea On-line Reliability Deployment Price Adder (RTORDPA) values are included at the top of the table. table includes the LMP values (without Real-Time Price Adders), the LMP change from the previo SCED run, the RTORPA plus the RTORDPA plus the LMP value, and the RTORPA plus the RTORDPA t...

Search for Related Topic(s): Real-Time Market | Locational Marginal Price(LMP) | Security-Constrained Economic Dispatch(S

Real-Time LMPs for Load Zones and Trading Hubs Display

A display of the latest SCED Locational Marginal Prices (LMPs) by Load Zone and Hub settlemen The latest on-line (RTORPA) and off-line (RTOFFPA) Real-Time Reserve Price Adder and the lates Time On-line Reliability Deployment Price Adder (RTORDPA) values are included at the top of the The table includes the LMP values (without Real-Time Price Adders), the LMP change from the p SCED run, the RTORPA plus the RTORDPA plus the LMP value, and the RTORPA plus the RTORDP

Search for Related Topic(s): Locational Marginal Price(LMP) | Security-Constrained Economic Dispatch(SCED) | Real-Time M

Real-Time Locational Prices

The Real-Time Locational Prices dashboard offers a dynamic view of Real-Time resource node Locational Marginal Prices (LMPs) and both Day-Ahead Market and Real-Time Settlement Point throughout the ERCOT region.

Search for Related Topic(s): Locational Marginal Price(LMP)

[EMIL (ercot.com)]

Dataset: 10_policy

Electricity policies:

[AEP Texas Energy Incentive Programs | Residential & Commercial (quickelectricity.com)]

EV policies:

[Alternative Fuels Data Center: Data Downloads (energy.gov)]

Energy policies:

[Database of State Incentives for Renewables & Efficiency® - DSIRE (dsireusa.org)]

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Prerequisite for Agent based modeling

» Identify key variables and agents:

- » key variables and agents to consider:
  - Demographic characteristics of residents (e.g. income, age, race, gender)
  - Availability and cost of charging infrastructure Statewide Planning Map (txdot.gov)
  - Transportation options (e.g. public transit, car ownership)
  - Energy usage patterns (e.g. electricity demand) **MDAT (census.gov)**
  - Environmental attitudes and awareness (e.g. education)
  - Policies and regulations related to EV charging and energy equity
- » Find underlying variables and agents:
  - » Collect as more data as possible
  - » Conduct statistical/Machine learning modelling to identify latent features/variables

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Ideas

Bigger data

- Collect as much data as possible, since much more data become available

Topics

- Coupling (interaction) effect of electricity and EV policy on equity of EV charging station distribution.
- (Economic Benefits) How advancing EV adoption rate in underrepresented communities can boost local economy growth in the long run. (to come up with more specific question in terms of the first topic)
- Underlying relations among EV charging stations, grid and building energy as well as demographic data.
- More?

Interaction among multiple agents

Metrics/criteria

New modeling approaches

- Data driven approach
- ML with ABM (later)

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Next Steps

Data Collection

- Manual data download
- Programmatic data download
- Data storage and management

Exploratory Data Analysis (EDA)

- Sanity Check
- Statistical analysis (descriptive statistics, inferential statistics, forecasting, A/B testing for different policies)
- Further specify the research topic
- Find underlying factors using ML
- Build predictive and ML models and serve as baseline model for validating ABM

Define agents, policies

Literature Review

- Conduct paper review while EDA
- Propose new ideas or specify topic

Validation

Agent Based Modeling

- Refine statistical models and machine learning models as a baseline
- Create ABM
- Integrate ABM with ML
- Validation
- Develop real-time dashboard app

Questions&Discussion

» which geographic area we focus on?

  » Texas Triangle

» Innovation/novelty:

  » new methodology

  » new social/economic/engineering problem

Project Framework

- Cluster Analysis
  - EDA:Quantitative analysis on inequality of EV adoption across different tracts.
    - innovation: combining sociodemographic, economic, political, and techno-infrastructural(EV, Electricity) factor
    - 2022 Inequality and the future of electric mobility in 36 U.S. Cities
  - Cluster analysis to determine factors/attributes affecting equality of EV adoption. Identify different typologies.
    - How inequality is Texas

LO0

- Machine Learning
  - Prediction on EV adoption rates across different tracts
    - How factors like electricity policy affect EV purchase decision
    - 2021 Classification of potential electric vehicle purchasers A ML approach
  - Change different policies as input
    - How should we tailor policies to different tracts/typologies, to achieve equity?

- ABM
  - BEAM Core with LBL/City of Dallas
  - C2C program with LBL/DFW

They use micro data, like block, household, need data from city of Dallas and a target community

- ML to help agent make decision
  - 2023 A framework proposal for ML-driven ABMs through a case study analysis.pdf

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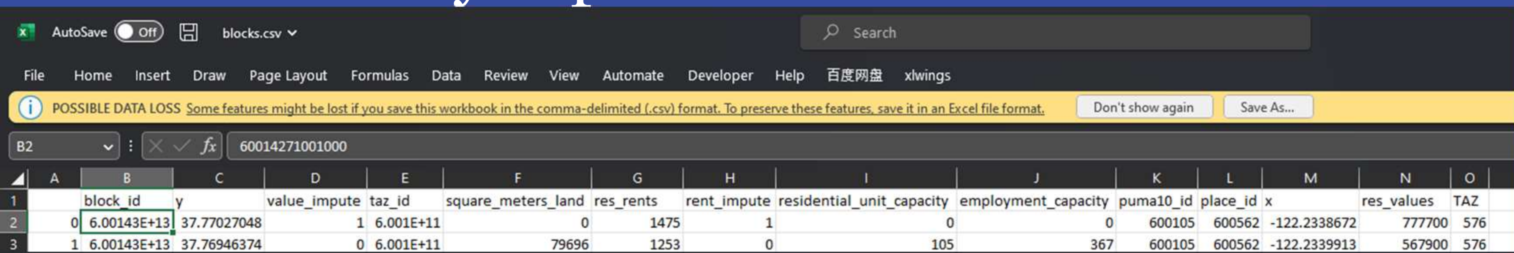
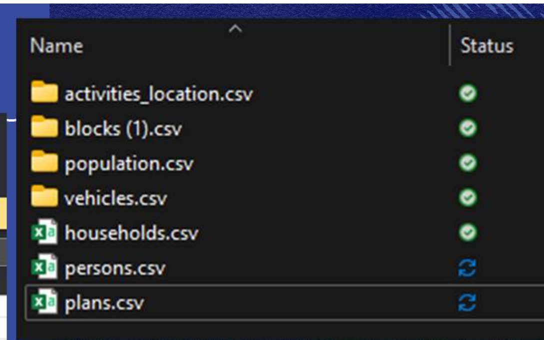
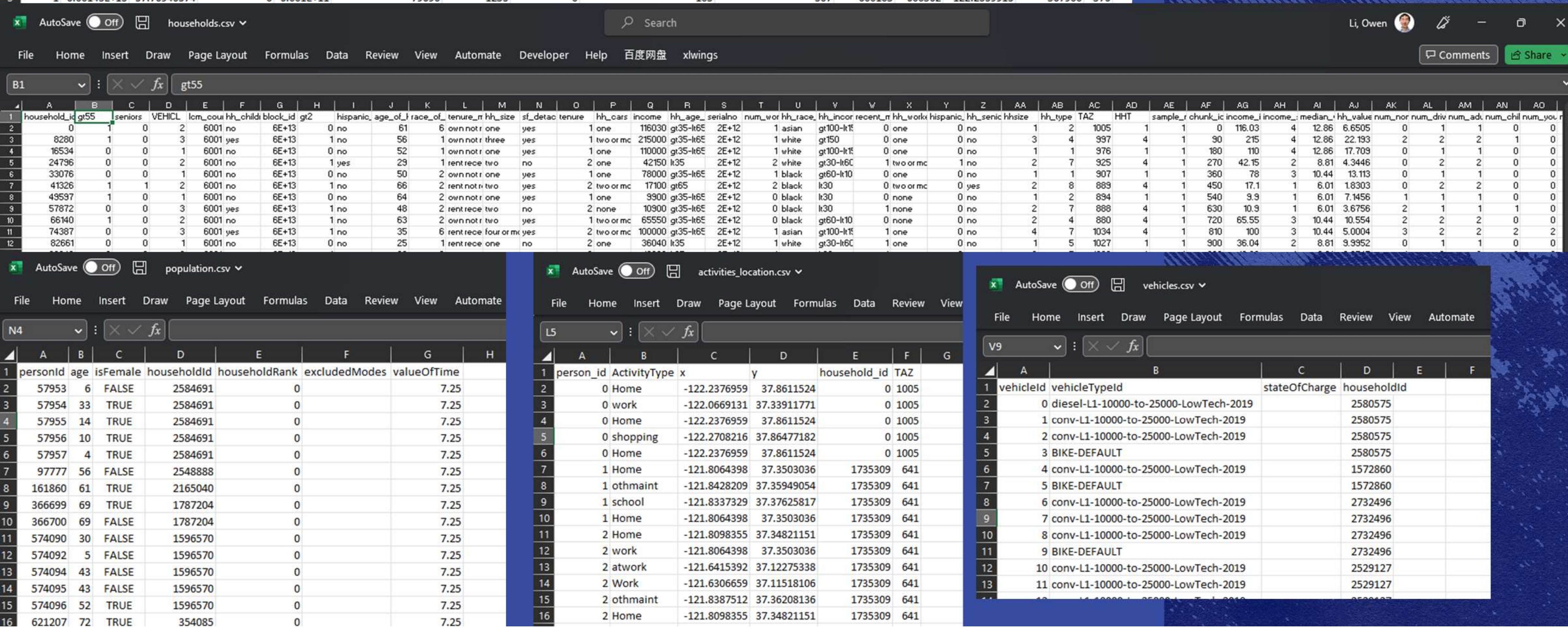
Slide 25

LO0 The data is all collected, and I have done EDA for US census. Others are in progress.
Li, Owen, 2023-04-06T21:32:10.687

BEAM activity inputs







BEAM network inputs

AutoSave Off init.linkstats.csv

File Home Insert Draw Page Layout Formulas Data Review View Automate Developer Help 百度网盘 xlwin

POSSIBLE DATA LOSS Some features might be lost if you save this workbook in the comma-delimited (.csv) format. To preserve these features, save it in a

S7

link	from	to	hour	length	freespeec	capacity	stat	volume	TruckVolu	HDTruckV	traveltime
144322	56666	10335	0	99.244	2.777778	300	AVG	0	0	0	35.72784
144322	56666	10335	1	99.244	2.777778	300	AVG	0	0	0	35.72784
144322	56666	10335	2	99.244	2.777778	300	AVG	0	0	0	35.72784
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144322	56666	10335	12	99.244	2.777778	300	AVG	0	0	0	35.72784
144322	56666	10335	13	99.244	2.777778	300	AVG	0	0	0	35.72784
144322	56666	10335	14	99.244	2.777778	300	AVG	0	0	0	35.72784
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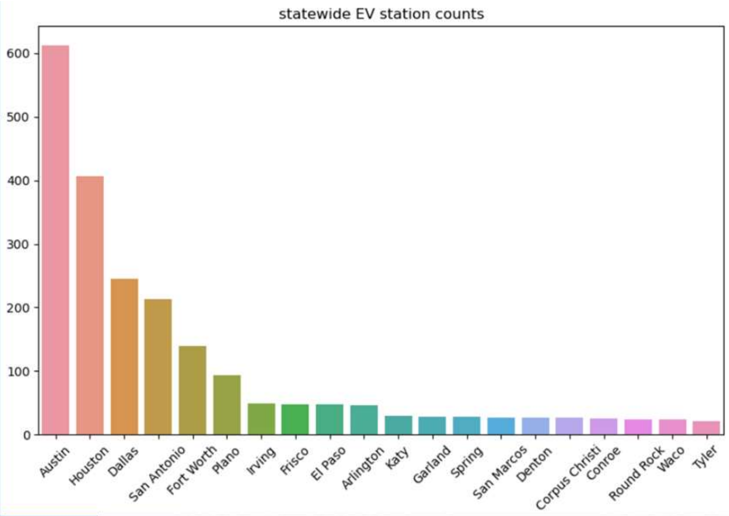
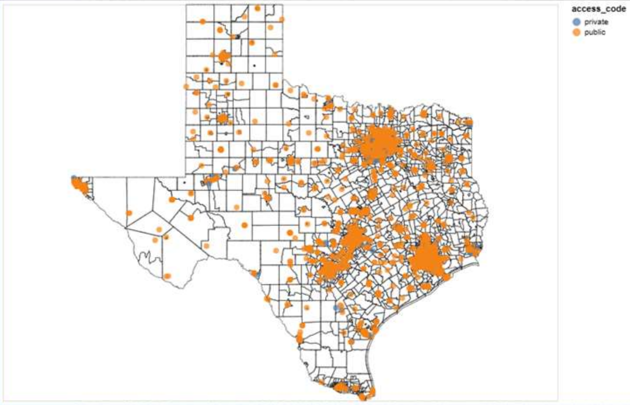
Finalize Data Source



- 2021 ACS social demographic data at tract level:
  - Kmean, hierarchical clustering, DBSCAN (silhouette score: below 0.05)
  - Nomailization (silhouette score: 0.15)
  - Dimension reduction (PCA) (silhouette score: ??)



- EV stations
- EV registration(light/medium/heavy duty)(not associate with location/tract/household)
- EV Law and incentives
- Electricity incentives
- Utility Rates by tract
- Twitter/facebook/Elsvier =>how people talk about EV policies.

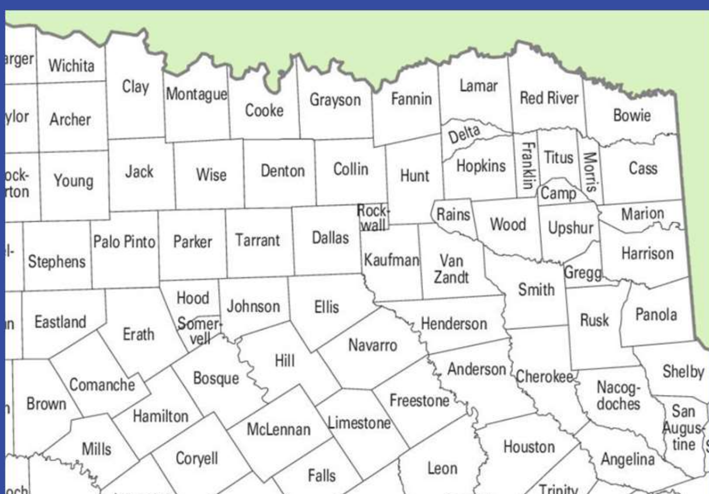
Dallas-Fort Worth

» Narrow down to DFW area(Dallas, Tarrant, Collin, Denton)

  » City of Dallas could provide more micro data if needed

  » Utility Rates by Census Region API has limits

  » DFW (Dallas, Tarrant, Collin, Denton) has 1507 tracts; Texas has 6896.



Questions to be answered

- Study how a certain incentive affects EV adoption in similar typologies at the same duration, using hypothesis testing
- What is the relationship between micro-typology and EV adoption(demand)?
- What is the correlations between EV adoption(demand) and incentives?
- How the same incentive affects different groups of people?
- Which combination of transportation and electricity policy would be most effective?
- Topic from City of Dallas/DFWcleancities
- ABM using BEAM, integrated RL/ML (course?)

5.2. Remaining Research Gaps

There are many areas remaining for further research on the impacts of managed charging on the grid, including:

- Testing different PEV adoption forecasts and different PEV fleet composition (e.g. vehicles with longer range).
- Testing different charging infrastructure scenarios, including the emphasis on fast versus slow charging, and added workplace charging infrastructure.
- Testing more accurate estimation of charging power constraints of the varying available charging infrastructure.
- Using California and/or National Household Travel Survey data to scale PEV charging demand and flexibility in a manner that reflects regional variations in mobility and charging infrastructure.
- Finding correlations between charging demand and mobility profiles (i.e. daily VMT) and including these relationships when scaling demand.
- Simulating the participation of aggregated PEV fleets in other grid services such as regulation and load-following through vehicle-to-grid.
- Testing different renewable renewable generation mixes.
- Testing the impact of competing sources of grid flexibility including increased storage and demand response, varied curtailment assumptions, and higher net export limits.

Finally, there are also many policy changes happening concurrently in California and WECC, which could impact the conclusions of this study. For example, California is already coordinating with neighboring balancing areas through the Energy Imbalance Market, which could alleviate some of the curtailment problems highlighted here [75]. CAISO may also expand to other parts of WECC, and there may be an increase in DR and load management from other end-uses besides PEVs to cope with curtailment. Lastly, there is a push to move residential electric customers in California to opt-out TOU rates in the next few years [83], which may incentivize load shifting during these curtailment periods, without the use of actively managed PEVs.

Next: may 10

Examine how many EV and EV stations typologies have?

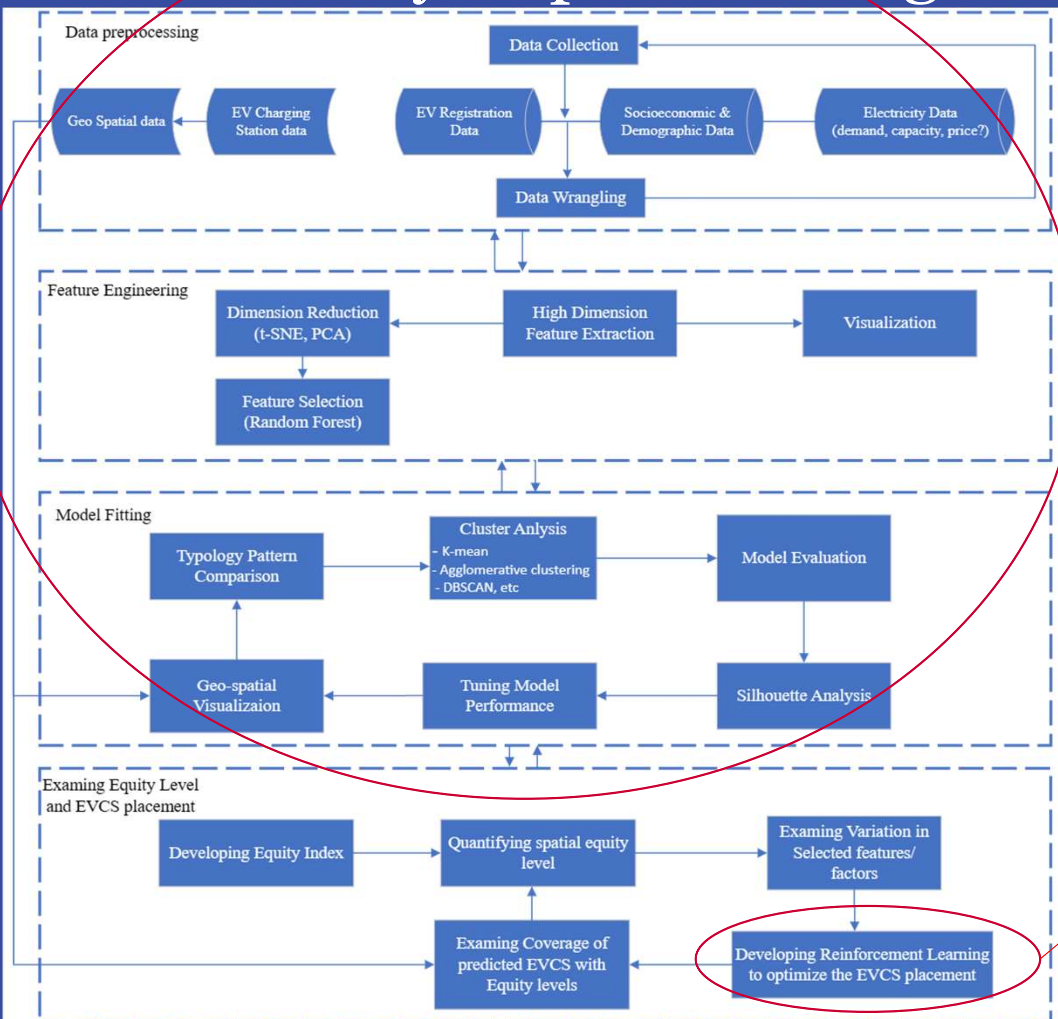
» Typology mapping by Tract ID

» EV stations mapping by Location

» EV registration by zipcode

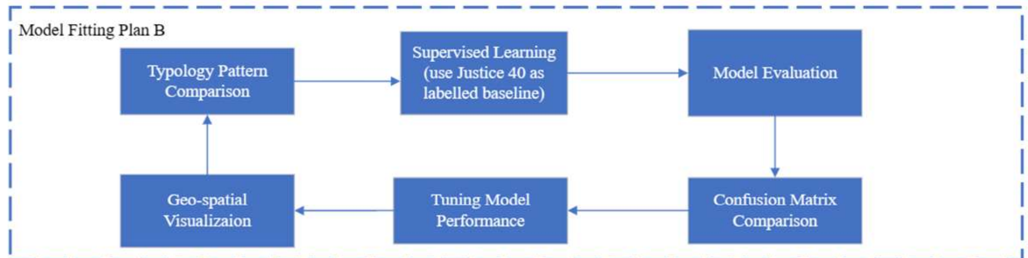
Cluster analysis process diagram

- Data Collection:
  - Dataset: Social Demographic dataset, Electricity dataset, EV registration dataset;
  - Geospatial mapping: Geospatial shapefile, EV charging station location;

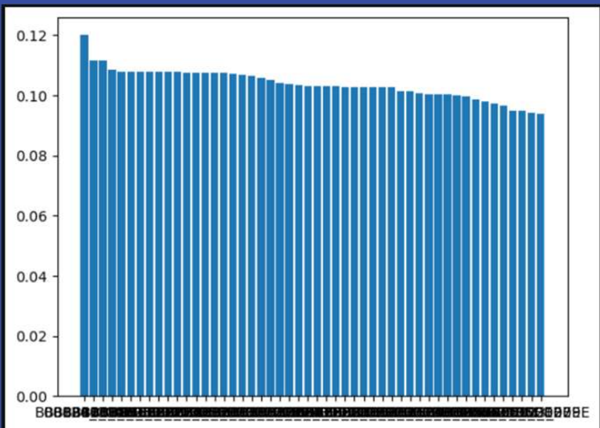


- Feature Engineering: the input data are high dimensional; we want to extract the most impactful features/attributes. We plan to use different dimension reduction techniques, to transform and select the features per the importance factor.

- Modelling fitting:
  - conduct the cluster analysis with consideration of the top important features;
  - Evaluate the clustering results via silhouette analysis;
  - Tuning hyperparameters to improve the results;
  - Visualize the clusters in the maps;
  - Compare different clustering results via patterns;
- Quantifying spatial equity level:
  - comparison between typologies pattern and EVCS placements;
  - develop equity metrics;
  - visualize the variations in equity level



- Develop multi-agent reinforcement learning algorithms to optimize the placement decision making:
  - The Multi-Agent System consists of macro and micro level agents, namely, DFW area agent and tract agents;
  - Design rewards based on the equity metrics;
  - Simulate the decision making process;
  - Discover and understand underlying trending, and make recommendation for policymakers



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B08124 : MEANS OF TRANSPORTATION TO WORK BY OCCUPATION
B08301 : MEANS OF TRANSPORTATION TO WORK
B08006 : SEX OF WORKERS BY MEANS OF TRANSPORTATION TO WORK
B08006 : SEX OF WORKERS BY MEANS OF TRANSPORTATION TO WORK
B11001 : HOUSEHOLD TYPE (INCLUDING LIVING ALONE)
B28010 : COMPUTERS IN HOUSEHOLD
B19001 : HOUSEHOLD INCOME IN THE PAST 12 MONTHS (IN 2021 INFLATION-ADJUSTED DOLLARS)
B28011 : INTERNET SUBSCRIPTIONS IN HOUSEHOLD
B25132 : MONTHLY ELECTRICITY COSTS
B25133 : MONTHLY GAS COSTS
B08122 : MEANS OF TRANSPORTATION TO WORK BY POVERTY STATUS IN THE PAST 12 MONTHS
B08126 : MEANS OF TRANSPORTATION TO WORK BY INDUSTRY
B08124 : MEANS OF TRANSPORTATION TO WORK BY OCCUPATION
B08006 : SEX OF WORKERS BY MEANS OF TRANSPORTATION TO WORK
B08301 : MEANS OF TRANSPORTATION TO WORK
B25132 : MONTHLY ELECTRICITY COSTS
B28010 : COMPUTERS IN HOUSEHOLD
B28011 : INTERNET SUBSCRIPTIONS IN HOUSEHOLD
B08303 : TRAVEL TIME TO WORK
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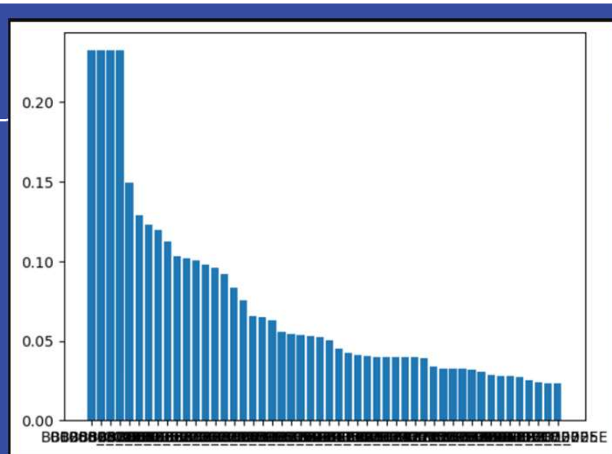

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B02001 : RACE
B05003 : SEX BY AGE BY NATIVITY AND CITIZENSHIP STATUS
B05001 : NATIVITY AND CITIZENSHIP STATUS IN THE UNITED STATES
B02001 : RACE
B05001 : NATIVITY AND CITIZENSHIP STATUS IN THE UNITED STATES
B02001 : RACE
B05003 : SEX BY AGE BY NATIVITY AND CITIZENSHIP STATUS
B05003 : SEX BY AGE BY NATIVITY AND CITIZENSHIP STATUS
B05003 : SEX BY AGE BY NATIVITY AND CITIZENSHIP STATUS
B15003 : EDUCATIONAL ATTAINMENT FOR THE POPULATION 25 YEARS AND OVER
B05001 : NATIVITY AND CITIZENSHIP STATUS IN THE UNITED STATES
B05003 : SEX BY AGE BY NATIVITY AND CITIZENSHIP STATUS
B05003 : SEX BY AGE BY NATIVITY AND CITIZENSHIP STATUS
B05003 : SEX BY AGE BY NATIVITY AND CITIZENSHIP STATUS
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B05003 : SEX BY AGE BY NATIVITY AND CITIZENSHIP STATUS
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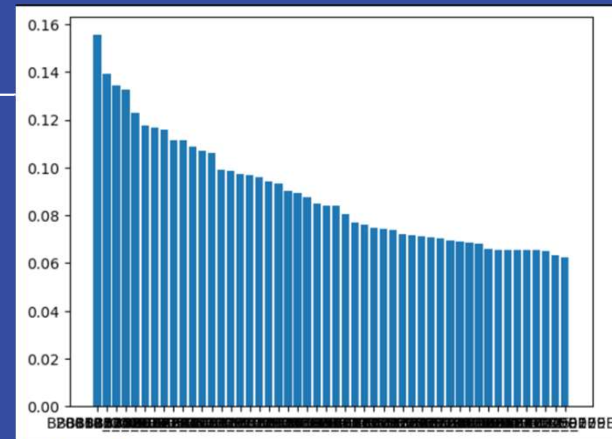

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B28010 : COMPUTERS IN HOUSEHOLD
B08122 : MEANS OF TRANSPORTATION TO WORK BY POVERTY STATUS IN THE PAST 12 MONTHS
B15003 : EDUCATIONAL ATTAINMENT FOR THE POPULATION 25 YEARS AND OVER
B08124 : MEANS OF TRANSPORTATION TO WORK BY OCCUPATION
B15003 : EDUCATIONAL ATTAINMENT FOR THE POPULATION 25 YEARS AND OVER
B17026 : RATIO OF INCOME TO POVERTY LEVEL OF FAMILIES IN THE PAST 12 MONTHS
B15003 : EDUCATIONAL ATTAINMENT FOR THE POPULATION 25 YEARS AND OVER
B08124 : MEANS OF TRANSPORTATION TO WORK BY OCCUPATION
B08122 : MEANS OF TRANSPORTATION TO WORK BY POVERTY STATUS IN THE PAST 12 MONTHS
B08124 : MEANS OF TRANSPORTATION TO WORK BY OCCUPATION
B08124 : MEANS OF TRANSPORTATION TO WORK BY OCCUPATION
B28011 : INTERNET SUBSCRIPTIONS IN HOUSEHOLD
B02001 : RACE
B15003 : EDUCATIONAL ATTAINMENT FOR THE POPULATION 25 YEARS AND OVER
B19001 : HOUSEHOLD INCOME IN THE PAST 12 MONTHS (IN 2021 INFLATION-ADJUSTED DOLLARS)
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B11001 : HOUSEHOLD TYPE (INCLUDING LIVING ALONE)
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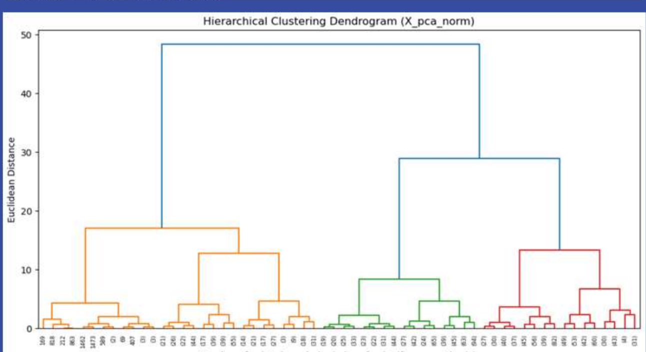
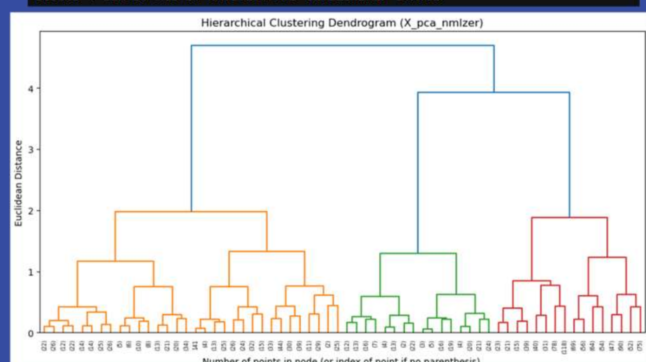
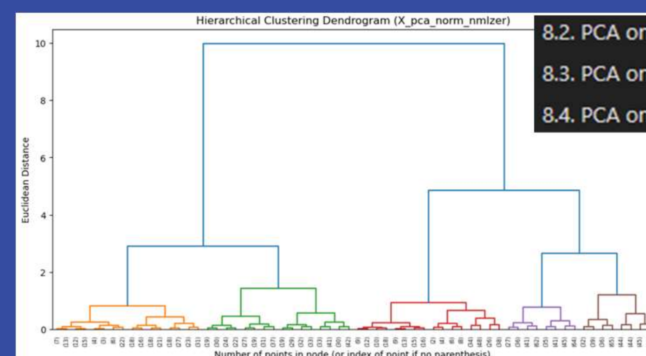


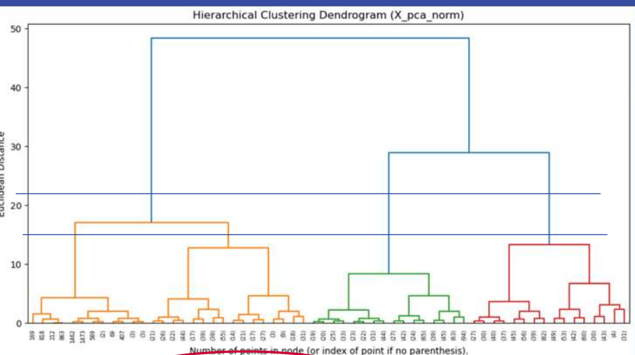


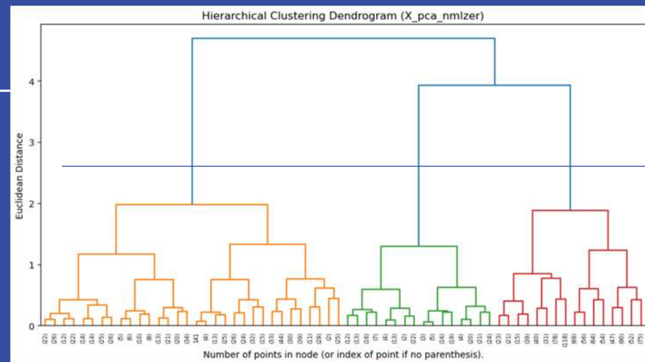


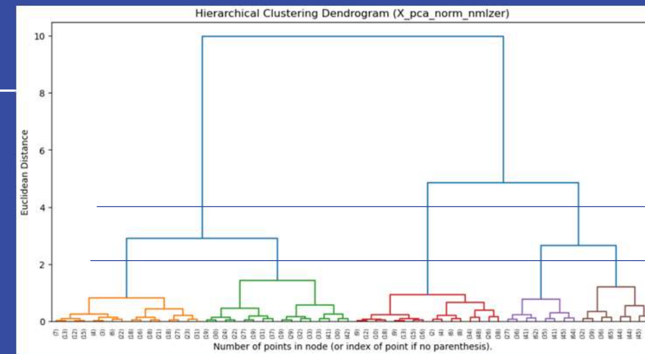
8.2. PCA on X_std

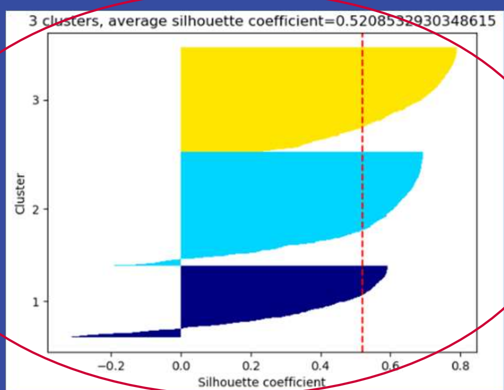
8.3. PCA on X_nmlzer

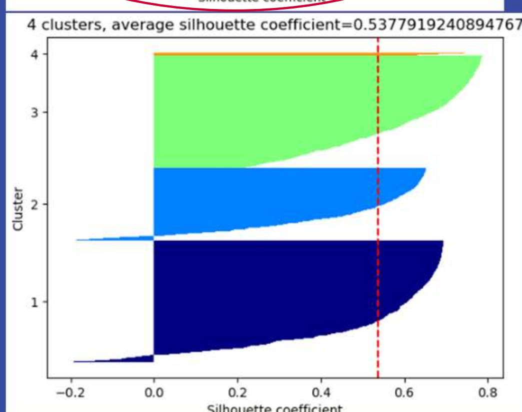
8.4. PCA on X_norm_nm

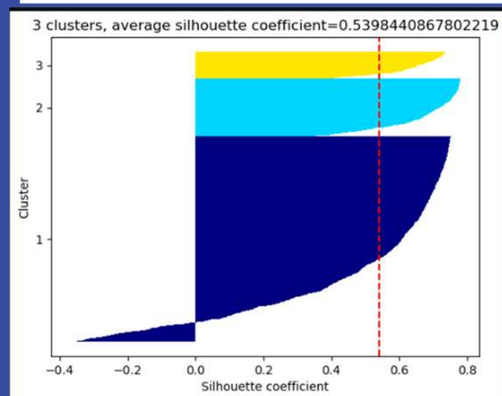


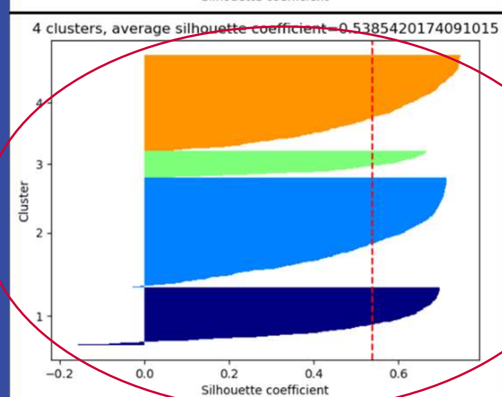


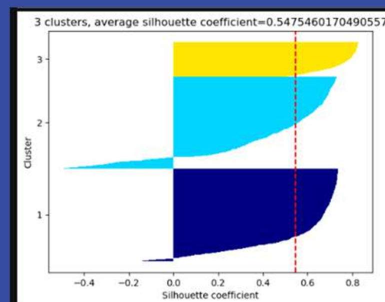


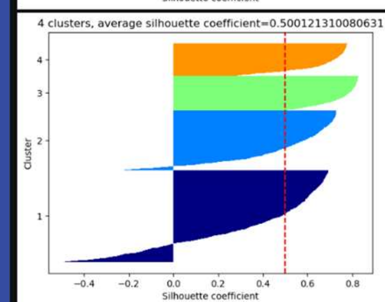


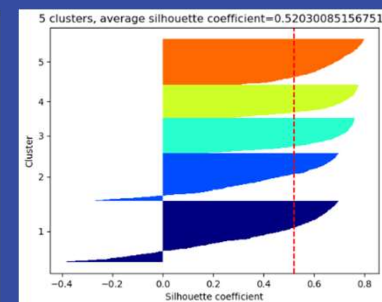


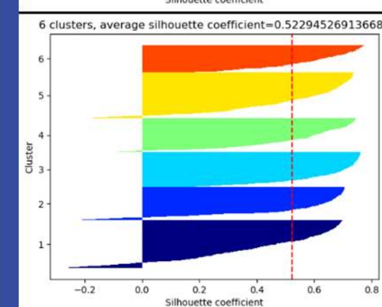






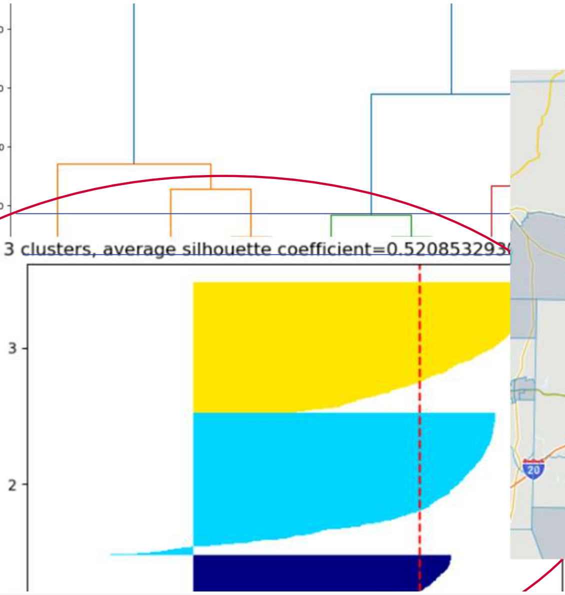


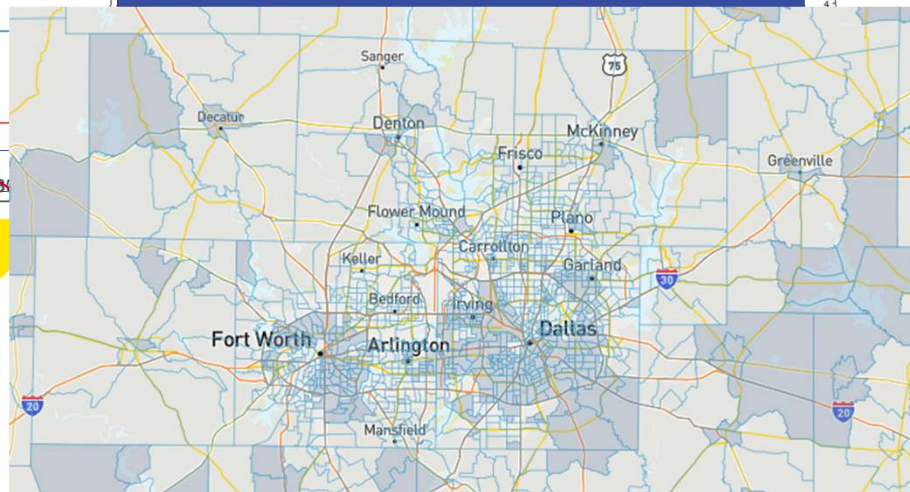


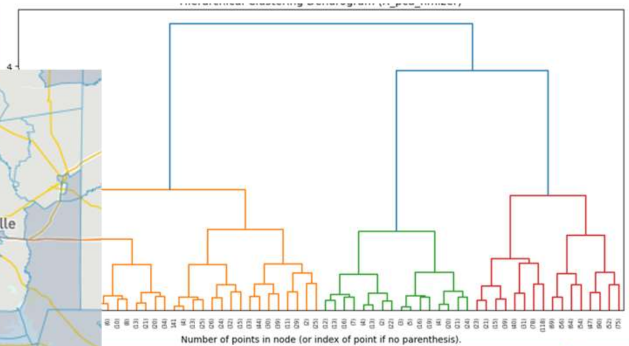


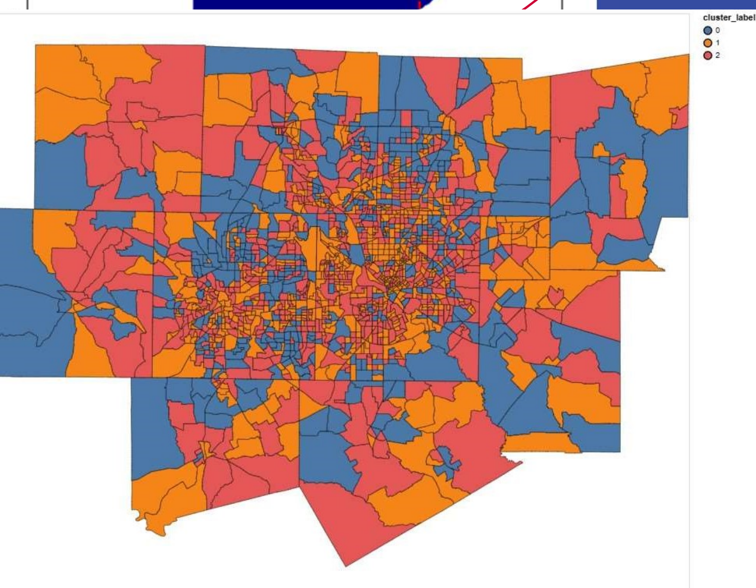
Other papers: less score, less features

SMU





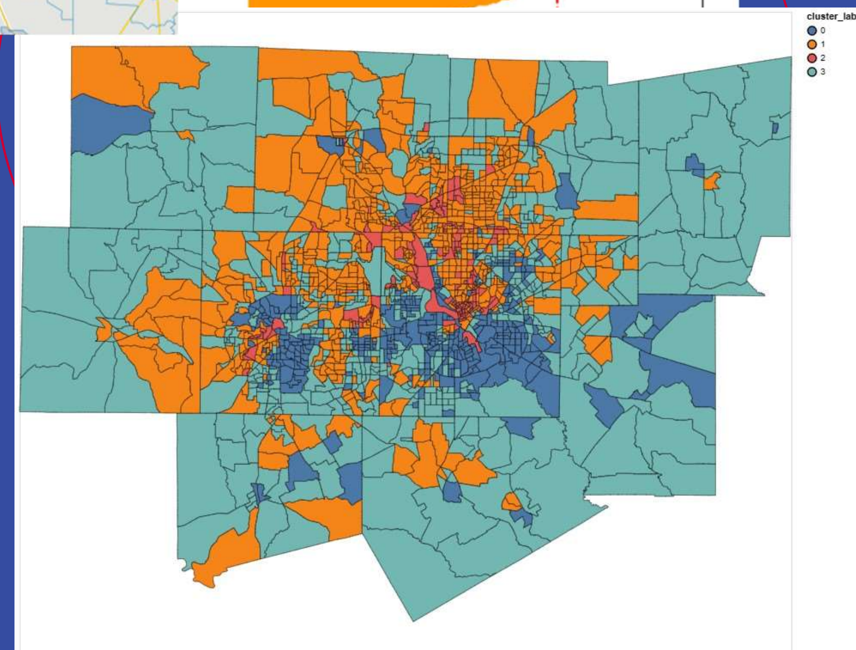


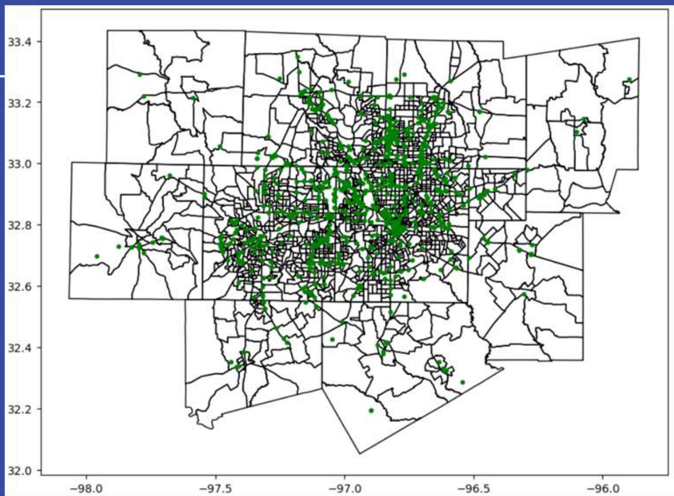


Justice 40

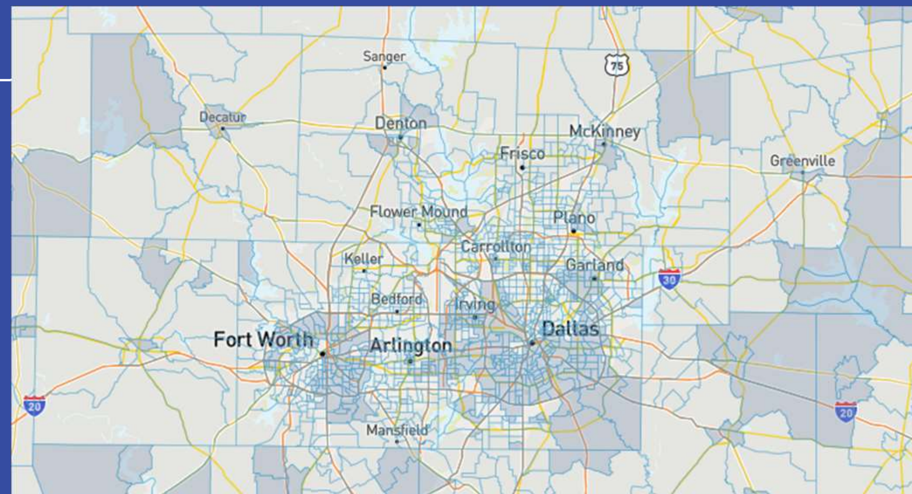
What are the social, economic, demographic, and techno factors that can quantify spatial inequity in EVCS placement?

Justice 40 is based on different factors

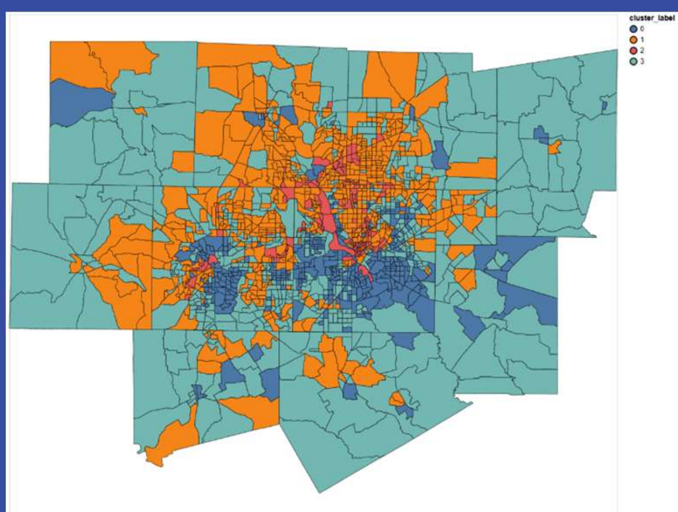


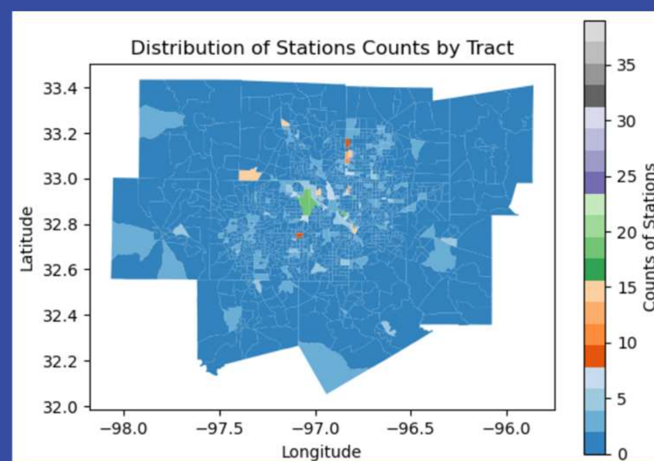


EVCS location



Justice 40 defined disadvantaged tracts





We may use our typology and/or Justice40

Is Justice40 a good fit for solving our problem, we don't know

In the end, we might have potential findings, like if using Justice 40 is good for EVCS placing decision making? Or the advantages of our typology

EVCS counts by Tract

Example Typologies

SMU

Feature importance from different algorithms

top_corr_attr(threshold = 0.2, correlation_matrix = merged_X_norm_EVCScnt.corr())

[54]:

	counts	Desc
counts	1.000000	0
B08122_020E	0.256632	[[Estimate, Total:, Walked:, At or above 150 percent of the poverty level]]
B08126_070E	0.249319	69 [Estimate, Total:, Walked:, Professional, scientific, and management, and administrative and waste management services] Name: Label, dtype: object
B08122_017E	0.243381	16 [Estimate, Total:, Walked:] Name: Label, dtype: object
B11001_007E	0.242668	6 [Estimate, Total:, Nonfamily households:] Name: Label, dtype: object
B08124_030E	0.241642	29 [Estimate, Total:, Walked:, Management, business, science, and arts occupations] Name: Label, dtype: object
B25132_005E	0.241469	4 [Estimate, Total, Charged for electricity, 50to99] Name: Label, dtype: object
B11001_008E	0.236092	7 [Estimate, Total:, Nonfamily households:, Householder living alone] Name: Label, dtype: object
B08006_032E	0.224437	31 [Estimate, Total:, Male:, Walked] Name: Label, dtype: object
B25132_004E	0.207955	3 [Estimate, Total, Charged for electricity, Less than $50] Name: Label, dtype: object
B08006_015E	0.202705	14 [Estimate, Total:, Walked] Name: Label, dtype: object
B08124_029E	0.202705	28 [Estimate, Total:, Walked:] Name: Label, dtype: object
B08126_061E	0.202705	60 [Estimate, Total:, Walked:] Name: Label, dtype: object
B08301_019E	0.202705	18 [Estimate, Total:, Walked] Name: Label, dtype: object

Correlation:

Correlation measures the statistical relationship between two variables. In the context of feature selection, you can compute the correlation between each feature and the target variable. Features with higher absolute correlation values (positive or negative) are considered more important.

Pros: Simple to compute, provides insight into linear relationships.

Cons: Only captures linear relationships, may miss complex interactions.

SMU

Feature importance from different algorithms

SelectKbest: f_regression

	Top Feature	score	p_values	Desc	Concept
4	B08126_070E	94.019891	1.507031e-21	69 [Estimate, Total:, Walked:, Professional, scientific, and management, and administrative and waste management services] Name: Label, dtype: object	69 MEANS OF TRANSPORTATION TO WORK BY INDUSTRY Name: Concept, dtype: object
3	B08124_030E	93.725772	1.731899e-21	29 [Estimate, Total:, Walked:, Management, business, science, and arts occupations] Name: Label, dtype: object	29 MEANS OF TRANSPORTATION TO WORK BY OCCUPATION Name: Concept, dtype: object
2	B08122_020E	87.892405	2.750332e-20	19 [Estimate, Total:, Walked:, At or above 150 percent of the poverty level] Name: Label, dtype: object	19 MEANS OF TRANSPORTATION TO WORK BY POVERTY STATUS IN THE PAST 12 MONTHS Name: Concept, dtype: object
1	B08122_017E	77.030604	4.905106e-18	16 [Estimate, Total:, Walked:] Name: Label, dtype: object	16 MEANS OF TRANSPORTATION TO WORK BY POVERTY STATUS IN THE PAST 12 MONTHS Name: Concept, dtype: object
6	B11001_007E	73.306123	2.933156e-17	6 [Estimate, Total:, Nonfamily households:] Name: Label, dtype: object	6 HOUSEHOLD TYPE (INCLUDING LIVING ALONE) Name: Concept, dtype: object
7	B11001_008E	70.450944	1.159946e-16	7 [Estimate, Total:, Nonfamily households:, Householder living alone] Name: Label, dtype: object	7 HOUSEHOLD TYPE (INCLUDING LIVING ALONE) Name: Concept, dtype: object
9	B25132_005E	68.930354	2.415743e-16	4 [Estimate, Total, Charged for electricity, 50to99] Name: Label, dtype: object	4 MONTHLY ELECTRICITY COSTS Name: Concept, dtype: object
0	B08006_032E	64.549367	2.011133e-15	31 [Estimate, Total:, Male:, Walked] Name: Label, dtype: object	31 SEX OF WORKERS BY MEANS OF TRANSPORTATION TO WORK Name: Concept, dtype: object
8	B25132_004E	58.219604	4.363616e-14	3 [Estimate, Total, Charged for electricity, Less than $50] Name: Label, dtype: object	3 MONTHLY ELECTRICITY COSTS Name: Concept, dtype: object
5	B08301_019E	53.278933	4.882910e-13	18 [Estimate, Total:, Walked] Name: Label, dtype: object	18 MEANS OF TRANSPORTATION TO WORK Name: Concept, dtype: object

SelectKbest: f_classif

	Top Feature	score	p_values	Desc	Conc
4	B08126_070E	94.019891	1.507031e-21	69 [Estimate, Total:, Walked:, Professional, scientific, and management, and administrative and waste management services] Name: Label, dtype: object	69 MEANS OF TRANSPORTATION TO WORK INDUSTRY Name: Concept, dtype: obj
3	B08124_030E	93.725772	1.731899e-21	29 [Estimate, Total:, Walked:, Management, business, science, and arts occupations] Name: Label, dtype: object	29 MEANS OF TRANSPORTATION TO WORK OCCUPATION Name: Concept, dtype: obj
2	B08122_020E	87.892405	2.750332e-20	19 [Estimate, Total:, Walked:, At or above 150 percent of the poverty level] Name: Label, dtype: object	19 MEANS OF TRANSPORTATION TO WORK POVERTY STATUS IN THE PAST 12 MONT Name: Concept, dtype: obj
1	B08122_017E	77.030604	4.905106e-18	16 [Estimate, Total:, Walked:] Name: Label, dtype: object	16 MEANS OF TRANSPORTATION TO WORK POVERTY STATUS IN THE PAST 12 MONT Name: Concept, dtype: obj
6	B11001_007E	73.306123	2.933156e-17	6 [Estimate, Total:, Nonfamily households:] Name: Label, dtype: object	6 HOUSEHOLD TYPE (INCLUDING LIVI ALONE) Name: Concept, dtype: obj
7	B11001_008E	70.450944	1.159946e-16	7 [Estimate, Total:, Nonfamily households:, Householder living alone] Name: Label, dtype: object	7 HOUSEHOLD TYPE (INCLUDING LIVI ALONE) Name: Concept, dtype: obj
9	B25132_005E	68.930354	2.415743e-16	4 [Estimate, Total, Charged for electricity, 50to99] Name: Label, dtype: object	4 MONTHLY ELECTRICITY COSTS Nar Concept, dtype: obj
0	B08006_032E	64.549367	2.011133e-15	31 [Estimate, Total:, Male:, Walked] Name: Label, dtype: object	31 SEX OF WORKERS BY MEANS TRANSPORTATION TO WORK Name: Conce dtype: obj
8	B25132_004E	58.219604	4.363616e-14	3 [Estimate, Total, Charged for electricity, Less than $50] Name: Label, dtype: object	3 MONTHLY ELECTRICITY COSTS Nar Concept, dtype: obj
5	B08301_019E	53.278933	4.882910e-13	18 [Estimate, Total:, Walked] Name: Label, dtype: object	18 MEANS OF TRANSPORTATION TO WO Name: Concept, dtype: obj

SelectKBest Score (ANOVA or Chi-Squared):

SelectKBest uses statistical tests (ANOVA F-values or chi-squared) to evaluate the relationship between each feature and the target variable. Features with higher scores are more likely to be informative for the target variable.

Pros: Systematic and principled approach, can handle categorical features.

Cons: May not capture complex non-linear relationships.

SMU

XGBoost

[321]:

	Top Feature	Importance	Desc	Concept
0	B05003_020E	0.079453	19 [Estimate, Total:, Female:, 18 years and over:, Native] Name: Label, dtype: object	19 SEX BY AGE BY NATIVITY AND CITIZENSHIP STATUS Name: Concept, dtype: object
1	B05001_002E	0.063960	1 [Estimate, Total:, U.S. citizen, born in the United States] Name: Label, dtype: object	1 NATIVITY AND CITIZENSHIP STATUS IN THE UNITED STATES Name: Concept, dtype: object
2	B08126_070E	0.037749	69 [Estimate, Total:, Walked:, Professional, scientific, and management, and administrative and waste management services] Name: Label, dtype: object	69 MEANS OF TRANSPORTATION TO WORK BY INDUSTRY Name: Concept, dtype: object
3	B08126_097E	0.037280	96 [Estimate, Total:, Worked from home:, Transportation and warehousing, and utilities] Name: Label, dtype: object	96 MEANS OF TRANSPORTATION TO WORK BY INDUSTRY Name: Concept, dtype: object
4	B08124_030E	0.034620	29 [Estimate, Total:, Walked:, Management, business, science, and arts occupations] Name: Label, dtype: object	29 MEANS OF TRANSPORTATION TO WORK BY OCCUPATION Name: Concept, dtype: object
5	B08126_041E	0.028934	40 [Estimate, Total:, Car, truck, or van - carpooled:, Educational services, and health care and social assistance] Name: Label, dtype: object	40 MEANS OF TRANSPORTATION TO WORK BY INDUSTRY Name: Concept, dtype: object
6	B11001_008E	0.024265	7 [Estimate, Total:, Nonfamily households:, Householder living alone] Name: Label, dtype: object	7 HOUSEHOLD TYPE (INCLUDING LIVING ALONE) Name: Concept, dtype: object
7	B08303_009E	0.024017	8 [Estimate, Total:, 35 to 39 minutes] Name: Label, dtype: object	8 TRAVEL TIME TO WORK Name: Concept, dtype: object
8	B05003_007E	0.022446	6 [Estimate, Total:, Male:, Under 18 years:, Foreign born:, Not a U.S. citizen] Name: Label, dtype: object	6 SEX BY AGE BY NATIVITY AND CITIZENSHIP STATUS Name: Concept, dtype: object
9	B28011_003E	0.020557	2 [Estimate, Total:, With an Internet subscription, Dial-up alone] Name: Label, dtype: object	2 INTERNET SUBSCRIPTIONS IN HOUSEHOLD Name: Concept, dtype: object

rf_FI(flag="reg")

			Desc	Concept
0	B08126_041E	0.045506	40 [Estimate, Total:, Car, truck, or van - carpooled:, Educational services, and health care and social assistance] Name: Label, dtype: object	40 MEANS OF TRANSPORTATION TO WORK BY INDUSTRY Name: Concept, dtype: object
1	B08126_070E	0.041445	69 [Estimate, Total:, Walked:, Professional, scientific, and management, and administrative and waste management services] Name: Label, dtype: object	69 MEANS OF TRANSPORTATION TO WORK BY INDUSTRY Name: Concept, dtype: object
2	B28011_003E	0.028419	2 [Estimate, Total:, With an Internet subscription, Dial-up alone] Name: Label, dtype: object	2 INTERNET SUBSCRIPTIONS IN HOUSEHOLD Name: Concept, dtype: object
3	B11001_007E	0.027914	6 [Estimate, Total:, Nonfamily households:] Name: Label, dtype: object	6 HOUSEHOLD TYPE (INCLUDING LIVING ALONE) Name: Concept, dtype: object
4	B11001_008E	0.027084	7 [Estimate, Total:, Nonfamily households:, Householder living alone] Name: Label, dtype: object	7 HOUSEHOLD TYPE (INCLUDING LIVING ALONE) Name: Concept, dtype: object
5	B08126_074E	0.024969	73 [Estimate, Total:, Walked:, Public administration] Name: Label, dtype: object	73 MEANS OF TRANSPORTATION TO WORK BY INDUSTRY Name: Concept, dtype: object
6	B05001_002E	0.022820	1 [Estimate, Total:, U.S. citizen, born in the United States] Name: Label, dtype: object	1 NATIVITY AND CITIZENSHIP STATUS IN THE UNITED STATES Name: Concept, dtype: object
7	B25132_005E	0.021347	4 [Estimate, Total, Charged for electricity, 50to99] Name: Label, dtype: object	4 MONTHLY ELECTRICITY COSTS Name: Concept, dtype: object
8	B08126_026E	0.020744	25 [Estimate, Total:, Car, truck, or van - drove alone:, Educational services, and health care and social assistance] Name: Label, dtype: object	25 MEANS OF TRANSPORTATION TO WORK BY INDUSTRY Name: Concept, dtype: object
9	B08124_030E	0.016790	29 [Estimate, Total:, Walked:, Management, business, science, and arts occupations] Name: Label, dtype: object	29 MEANS OF TRANSPORTATION TO WORK BY OCCUPATION Name: Concept, dtype: object

LightBoost

Pros: Captures non-linear relationships, interactions, and feature dependencies.

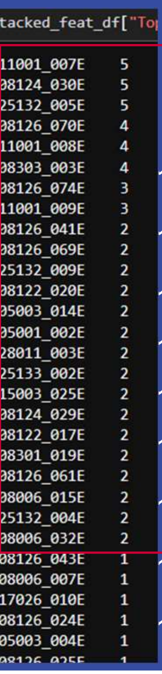
	Top Feature	Importance	Desc	Concept
0	B08126_024E	17	23 [Estimate, Total:, Car, truck, or van - drove alone:, Finance and insurance, and real estate and rental and leasing] Name: Label, dtype: object	23 MEANS OF TRANSPORTATION TO WORK BY INDUSTRY Name: Concept, dtype: object
1	B08303_003E	15	2 [Estimate, Total:, 5 to 9 minutes] Name: Label, dtype: object	2 TRAVEL TIME TO WORK Name: Concept, dtype: object
2	B08124_030E	11	29 [Estimate, Total:, Walked:, Management, business, science, and arts occupations] Name: Label, dtype: object	29 MEANS OF TRANSPORTATION TO WORK BY OCCUPATION Name: Concept, dtype: object
3	B08126_074E	9	73 [Estimate, Total:, Walked:, Public administration] Name: Label, dtype: object	73 MEANS OF TRANSPORTATION TO WORK BY INDUSTRY Name: Concept, dtype: object
4	B05003_004E	9	3 [Estimate, Total:, Male:, Under 18 years:, Native] Name: Label, dtype: object	3 SEX BY AGE BY NATIVITY AND CITIZENSHIP STATUS Name: Concept, dtype: object
5	B15003_025E	8	24 [Estimate, Total:, Doctorate degree] Name: Label, dtype: object	24 EDUCATIONAL ATTAINMENT FOR THE POPULATION 25 YEARS AND OVER Name: Concept, dtype: object
6	B08126_025E	8	24 [Estimate, Total:, Car, truck, or van - drove alone:, Professional, scientific, and management, and administrative and waste management services] Name: Label, dtype: object	24 MEANS OF TRANSPORTATION TO WORK BY INDUSTRY Name: Concept, dtype: object
7	B25132_009E	8	8 [Estimate, Total, Charged for electricity, $250 or more] Name: Label, dtype: object	8 MONTHLY ELECTRICITY COSTS Name: Concept, dtype: object
8	B19001_013E	8	12 [Estimate, Total:, 75,000to99,999] Name: Label, dtype: object	12 HOUSEHOLD INCOME IN THE PAST 12 MONTHS (IN 2021 INFLATION-ADJUSTED DOLLARS) Name: Concept, dtype: object
9	B08126_043E	8	42 [Estimate, Total:, Car, truck, or van - carpooled:, Other services (except public administration)] Name: Label, dtype: object	42 MEANS OF TRANSPORTATION TO WORK BY INDUSTRY Name: Concept, dtype: object
10	B02001_004E	7	3 [Estimate, Total:, American Indian and Alaska Native alone] Name: Label, dtype: object	3 RACE Name: Concept, dtype: object

rf_FI(flag="clf")

	Top Feature	Importance	Desc	Concept
0	B08303_003E	0.011266	2 [Estimate, Total:, 5 to 9 minutes] Name: Label, dtype: object	2 TRAVEL TIME TO WORK Name: Concept, dtype: object
1	B25132_005E	0.007752	4 [Estimate, Total, Charged for electricity, 50to99] Name: Label, dtype: object	4 MONTHLY ELECTRICITY COSTS Name: Concept, dtype: object
2	B25132_009E	0.006329	8 [Estimate, Total, Charged for electricity, $250 or more] Name: Label, dtype: object	8 MONTHLY ELECTRICITY COSTS Name: Concept, dtype: object
3	B11001_007E	0.006308	6 [Estimate, Total:, Nonfamily households:] Name: Label, dtype: object	6 HOUSEHOLD TYPE (INCLUDING LIVING ALONE) Name: Concept, dtype: object
4	B11001_008E	0.005864	7 [Estimate, Total:, Nonfamily households:, Householder living alone] Name: Label, dtype: object	7 HOUSEHOLD TYPE (INCLUDING LIVING ALONE) Name: Concept, dtype: object
5	B11001_009E	0.005853	8 [Estimate, Total:, Nonfamily households:, Householder not living alone] Name: Label, dtype: object	8 HOUSEHOLD TYPE (INCLUDING LIVING ALONE) Name: Concept, dtype: object
6	B08124_030E	0.005624	29 [Estimate, Total:, Walked:, Management, business, science, and arts occupations] Name: Label, dtype: object	29 MEANS OF TRANSPORTATION TO WORK BY OCCUPATION Name: Concept, dtype: object
7	B25132_004E	0.005430	3 [Estimate, Total, Charged for electricity, Less than $50] Name: Label, dtype: object	3 MONTHLY ELECTRICITY COSTS Name: Concept, dtype: object
8	B25133_005E	0.005103	4 [Estimate, Total, Charged for gas, 25to49] Name: Label, dtype: object	4 MONTHLY GAS COSTS Name: Concept, dtype: object
9	B08303_005E	0.005099	4 [Estimate, Total:, 15 to 19 minutes] Name: Label, dtype: object	4 TRAVEL TIME TO WORK Name: Concept, dtype: object

Combine most frequent yet significant features from various algo

Features		Desc	Concept
0	B11001_007E	6 [Estimate, Total:, Nonfamily households:] Name: Label, dtype: object	6 HOUSEHOLD TYPE (INCLUDING LIVING ALONE) Name: Concept, dtype: object
1	B08124_030E	29 [Estimate, Total:, Walked:, Management, business, science, and arts occupations] Name: Label, dtype: object	29 MEANS OF TRANSPORTATION TO WORK BY OCCUPATION Name: Concept, dtype: object
2	B25132_005E	4 [Estimate, Total, Charged for electricity, 50𝑡𝑜50��99] Name: Label, dtype: object	4 MONTHLY ELECTRICITY COSTS Name: Concept, dtype: object
3	B08126_070E	69 [Estimate, Total:, Walked:, Professional, scientific, and management, and administrative and waste management services] Name: Label, dtype: object	69 MEANS OF TRANSPORTATION TO WORK BY INDUSTRY Name: Concept, dtype: object
4	B11001_008E	7 [Estimate, Total:, Nonfamily households:, Householder living alone] Name: Label, dtype: object	7 HOUSEHOLD TYPE (INCLUDING LIVING ALONE) Name: Concept, dtype: object
5	B08303_003E	2 [Estimate, Total:, 5 to 9 minutes] Name: Label, dtype: object	2 TRAVEL TIME TO WORK Name: Concept, dtype: object
6	B08126_074E	73 [Estimate, Total:, Walked:, Public administration] Name: Label, dtype: object	73 MEANS OF TRANSPORTATION TO WORK BY INDUSTRY Name: Concept, dtype: object
7	B11001_009E	8 [Estimate, Total:, Nonfamily households:, Householder not living alone] Name: Label, dtype: object	8 HOUSEHOLD TYPE (INCLUDING LIVING ALONE) Name: Concept, dtype: object
8	B08126_041E	40 [Estimate, Total:, Car, truck, or van - carpooled:, Educational services, and health care and social assistance] Name: Label, dtype: object	40 MEANS OF TRANSPORTATION TO WORK BY INDUSTRY Name: Concept, dtype: object
9	B08126_069E	68 [Estimate, Total:, Walked:, Finance and insurance, and real estate and rental and leasing] Name: Label, dtype: object	68 MEANS OF TRANSPORTATION TO WORK BY INDUSTRY Name: Concept, dtype: object
10	B25132_009E	8 [Estimate, Total, Charged for electricity, $250 or more] Name: Label, dtype: object	8 MONTHLY ELECTRICITY COSTS Name: Concept, dtype: object
11	B08122_020E	19 [Estimate, Total:, Walked:, At or above 150 percent of the poverty level] Name: Label, dtype: object	19 MEANS OF TRANSPORTATION TO WORK BY POVERTY STATUS IN THE PAST 12 MONTHS Name: Concept, dtype: object
12	B05003_014E	13 [Estimate, Total:, Female:, Under 18 years:] Name: Label, dtype: object	13 SEX BY AGE BY NATIVITY AND CITIZENSHIP STATUS Name: Concept, dtype: object
13	B05001_002E	1 [Estimate, Total:, U.S. citizen, born in the United States] Name: Label, dtype: object	1 NATIVITY AND CITIZENSHIP STATUS IN THE UNITED STATES Name: Concept, dtype: object
14	B28011_003E	2 [Estimate, Total:, With an Internet subscription, Dial-up alone] Name: Label, dtype: object	2 INTERNET SUBSCRIPTIONS IN HOUSEHOLD Name: Concept, dtype: object
15	B25133_002E	1 [Estimate, Total, Not charged, not used, or payment included in other fees] Name: Label, dtype: object	1 MONTHLY GAS COSTS Name: Concept, dtype: object
16	B15003_025E	24 [Estimate, Total:, Doctorate degree] Name: Label, dtype: object	24 EDUCATIONAL ATTAINMENT FOR THE POPULATION 25 YEARS AND OVER Name: Concept, dtype: object
17	B08124_029E	28 [Estimate, Total:, Walked:] Name: Label, dtype: object	28 MEANS OF TRANSPORTATION TO WORK BY OCCUPATION Name: Concept, dtype: object
18	B08122_017E	16 [Estimate, Total:, Walked:] Name: Label, dtype: object	16 MEANS OF TRANSPORTA[illegible] BY POVERTY STATUS IN THE PAST [illegible] Concept, dtype: object

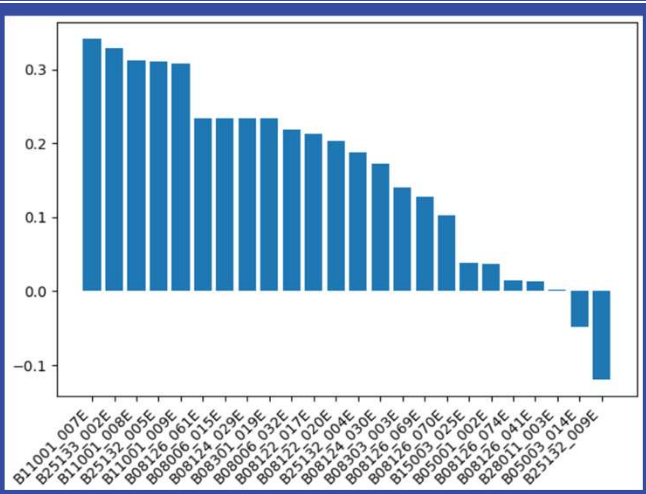


Feature Extraction using PCA based on Combined Feature Selection

» Keep 1st principal component

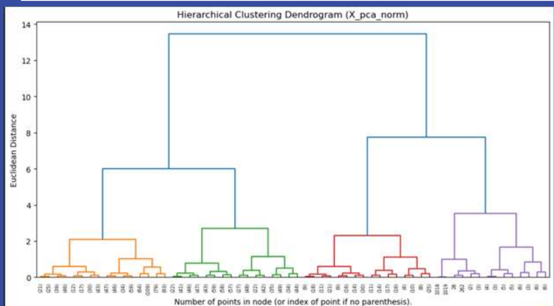
Interesting Findings:

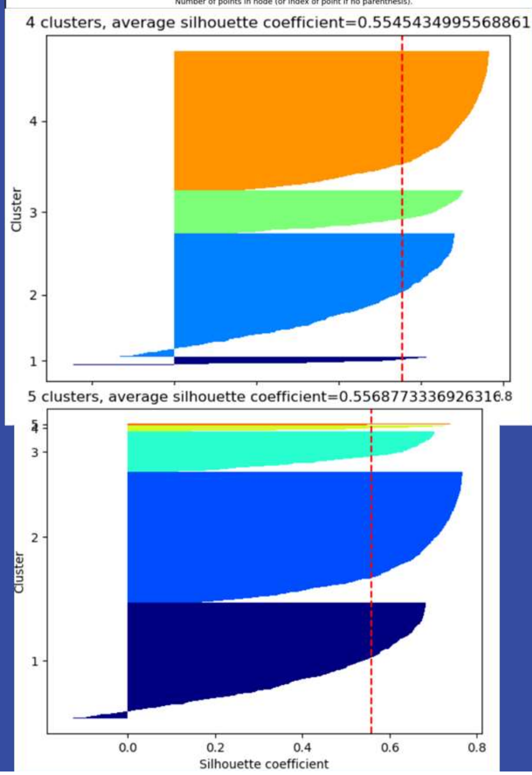
1) Non-family households, walk to work or 5 to 9 mins drive to work, less gas and electricity monthly cost
2) Race does not significantly impact
3) Females under 18 has less accessibility
4) Higher charge for electricity leading to less EVCS

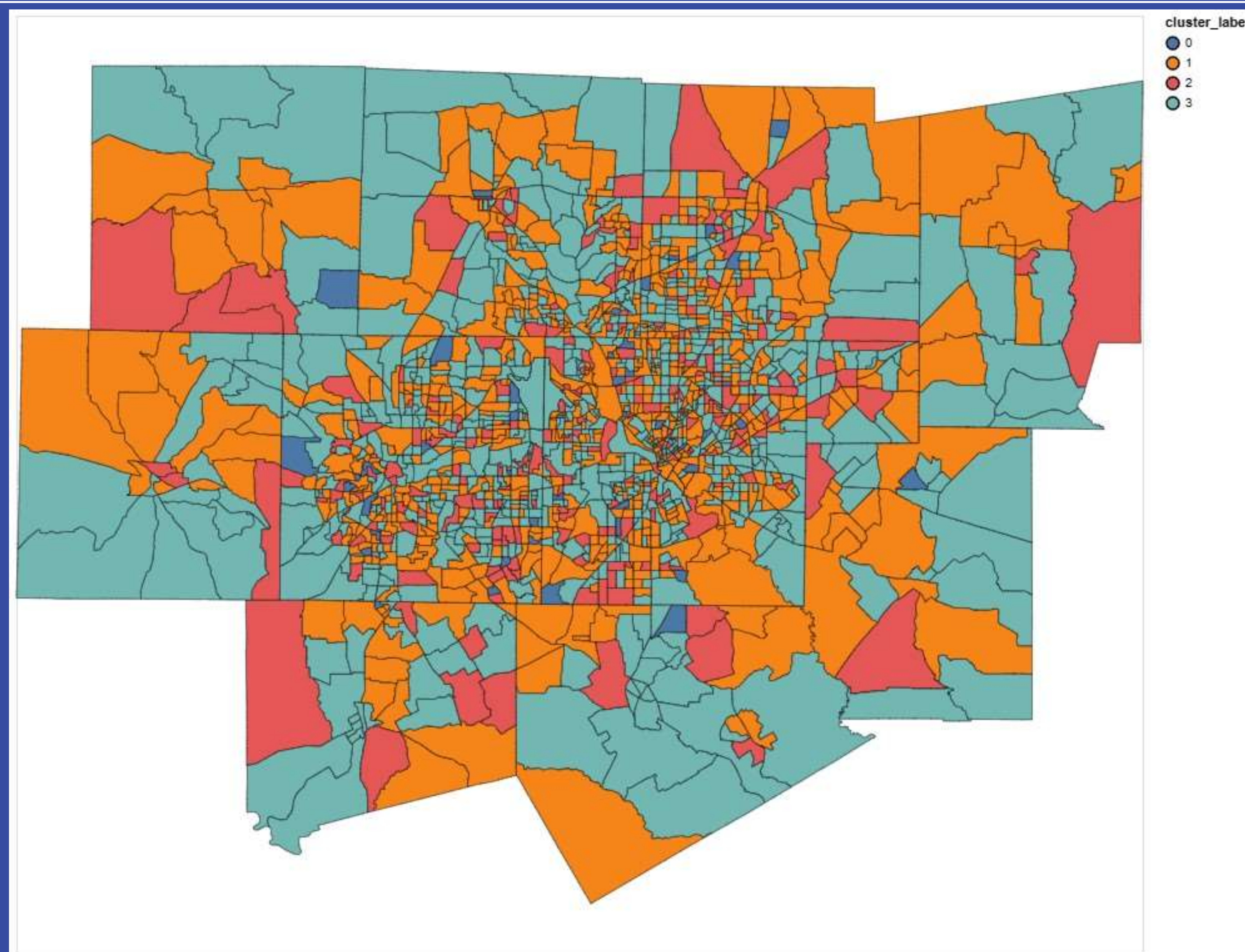


	features	contribution	Desc	Concept
0	B11001_007E	0.341022	6 Estimate!!Total:!!Nonfamily households: Name: Label, dtype: object	6 HOUSEHOLD TYPE (INCLUDING LIVING ALONE) Name: Concept, dtype: object
1	B25133_002E	0.329319	1 Estimate!!Total!!Not charged, not used, or payment included in other fees Name: Label, dtype: object	1 MONTHLY GAS COSTS Name: Concept, dtype: object
2	B11001_008E	0.312600	7 Estimate!!Total:!!Nonfamily households:!!Householder living alone Name: Label, dtype: object	7 HOUSEHOLD TYPE (INCLUDING LIVING ALONE) Name: Concept, dtype: object
3	B25132_005E	0.311248	4 Estimate!!Total!!Charged for electricity!!50to99 Name: Label, dtype: object	4 MONTHLY ELECTRICITY COSTS Name: Concept, dtype: object
4	B11001_009E	0.308270	8 Estimate!!Total:!!Nonfamily households:!!Householder not living alone Name: Label, dtype: object	8 HOUSEHOLD TYPE (INCLUDING LIVING ALONE) Name: Concept, dtype: object
5	B08126_061E	0.234539	60 Estimate!!Total:!!Walked: Name: Label, dtype: object	60 MEANS OF TRANSPORTATION TO WORK BY INDUSTRY Name: Concept, dtype: object
6	B08006_015E	0.234539	14 Estimate!!Total:!!Walked Name: Label, dtype: object	14 SEX OF WORKERS BY MEANS OF TRANSPORTATION TO WORK Name: Concept, dtype: object
7	B08124_029E	0.234539	28 Estimate!!Total:!!Walked: Name: Label, dtype: object	28 MEANS OF TRANSPORTATION TO WORK BY OCCUPATION Name: Concept, dtype: object
8	B08301_019E	0.234539	18 Estimate!!Total:!!Walked Name: Label, dtype: object	18 MEANS OF TRANSPORTATION TO WORK Name: Concept, dtype: object
9	B08006_032E	0.217987	31 Estimate!!Total:!!Male:!!Walked Name: Label, dtype: object	31 SEX OF WORKERS BY MEANS OF TRANSPORTATION TO WORK Name: Concept, dtype: object
10	B08122_017E	0.213197	16 Estimate!!Total:!!Walked: Name: Label, dtype: object	16 MEANS OF TRANSPORTATION TO WORK BY POVERTY STATUS IN THE PAST 12 MONTHS Name: Concept, dtype: object
11	B08122_020E	0.203795	19 Estimate!!Total:!!Walked:!!At or above 150 percent of the poverty level Name: Label, dtype: object	19 MEANS OF TRANSPORTATION TO WORK BY POVERTY STATUS IN THE PAST 12 MONTHS Name: Concept, dtype: object
12	B25132_004E	0.188267	3 Estimate!!Total!!Charged for electricity!!Less than $50 Name: Label, dtype: object	3 MONTHLY ELECTRICITY COSTS Name: Concept, dtype: object
13	B08124_030E	0.172386	29 Estimate!!Total:!!Walked:!!Management, business, science, and arts occupations Name: Label, dtype: object	29 MEANS OF TRANSPORTATION TO WORK B OCCUPATION Name: Concept, dtype: objec
14	B08303_003E	0.139835	2 Estimate!!Total:!!5 to 9 minutes Name: Label, dtype: object	2 TRAVEL TIME TO WORK Name: Concept, dtype: objec
15	B08126_069E	0.127180	68 Estimate!!Total:!!Walked:!!Finance and insurance, and real estate and rental and leasing Name: Label, dtype: object	68 MEANS OF TRANSPORTATION TO WORK B INDUSTRY Name: Concept, dtype: objec
16	B08126_070E	0.102291	69 Estimate!!Total:!!Walked:!!Professional, scientific, and management, and administrative and waste management services Name: Label, dtype: object	69 MEANS OF TRANSPORTATION TO WORK B INDUSTRY Name: Concept, dtype: objec
17	B15003_025E	0.037847	24 Estimate!!Total:!!Doctorate degree Name: Label, dtype: object	24 EDUCATIONAL ATTAINMENT FOR THE POPULATIO 25 YEARS AND OVER Name: Concept, dtype: objec
18	B05001_002E	0.036872	1 Estimate!!Total:!!U.S. citizen, born in the United States Name: Label, dtype: object	1 NATIVITY AND CITIZENSHIP STATUS IN THE UNITE STATES Name: Concept, dtype: objec
19	B08126_074E	0.014360	73 Estimate!!Total:!!Walked:!!Public administration Name: Label, dtype: object	73 MEANS OF TRANSPORTATION TO WORK B INDUSTRY Name: Concept, dtype: objec
20	B08126_041E	0.013217	40 Estimate!!Total:!!Car, truck, or van - carpooled:!!Educational services, and health care and social assistance Name: Label, dtype: object	40 MEANS OF TRANSPORTATION TO WORK B INDUSTRY Name: Concept, dtype: objec
21	B28011_003E	0.001944	2 Estimate!!Total:!!With an Internet subscription!!Dial-up alone Name: Label, dtype: object	2 INTERNET SUBSCRIPTIONS IN HOUSEHOLD Name Concept, dtype: objec
22	B05003_014E	-0.048422	13 Estimate!!Total:!!Female:!!Under 18 years: Name: Label, dtype: object	13 SEX BY AGE BY NATIVITY AND CITIZENSHIP STATU Name: Concept, dtype: objec
23	B25132_009E	-0.119232	8 Estimate!!Total!!Charged for electricity!!$250 or more Name: Label, dtype: object	8 MONTHLY ELECTRICITY COSTS Name: Concept, dtype objec

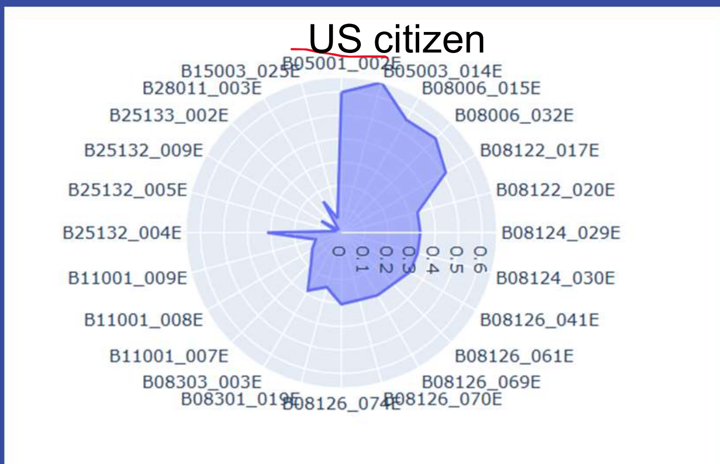
Clustering

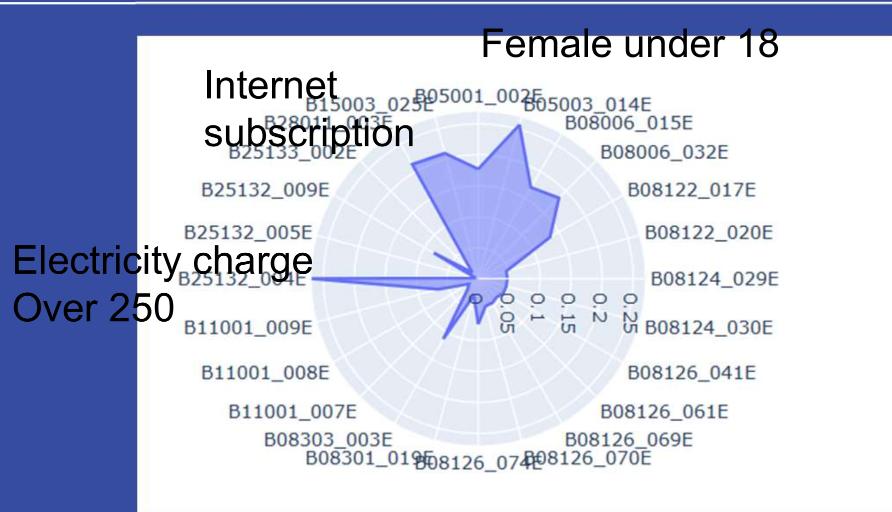

Hierarchical Clustering Dendrogram (X_pca_norm)
Euclidean Distance
Number of points in node (or index of point if no parenthesis).

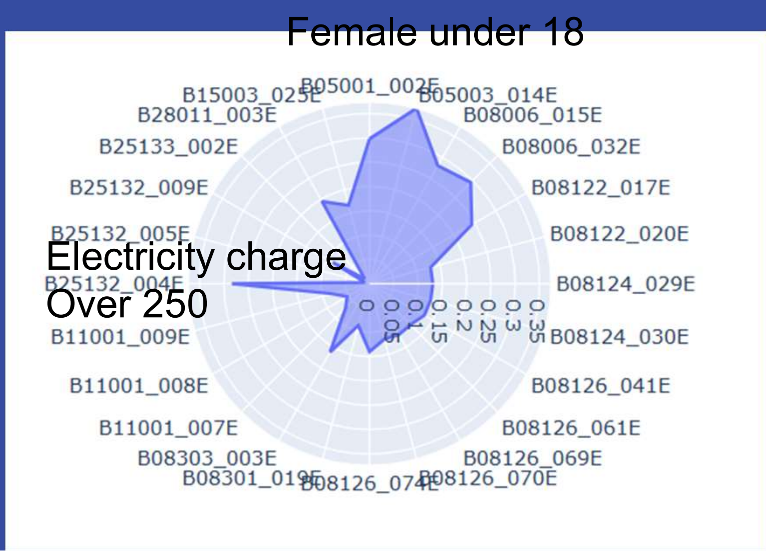

4 clusters, average silhouette coefficient=0.5545434995568861
Cluster
5 clusters, average silhouette coefficient=0.5568773336926316
Cluster
Silhouette coefficient

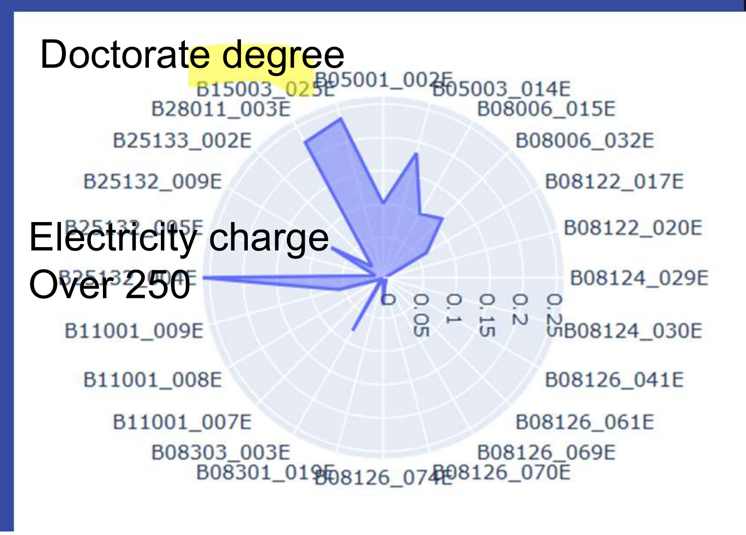

cluster_label
0
1
2
3

Characteristics of Typologies





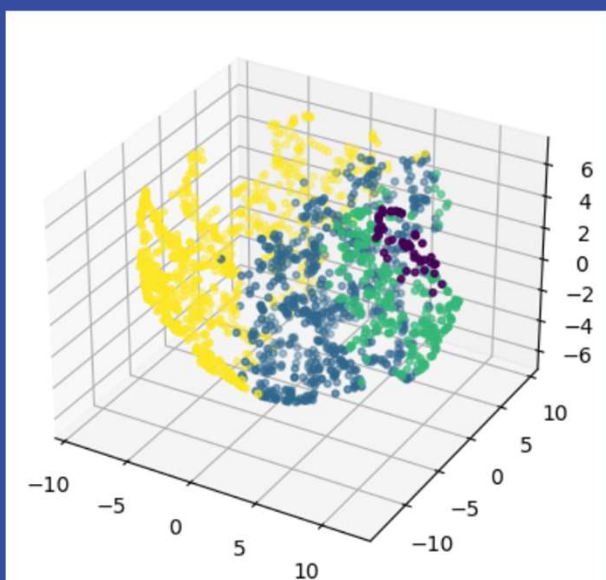


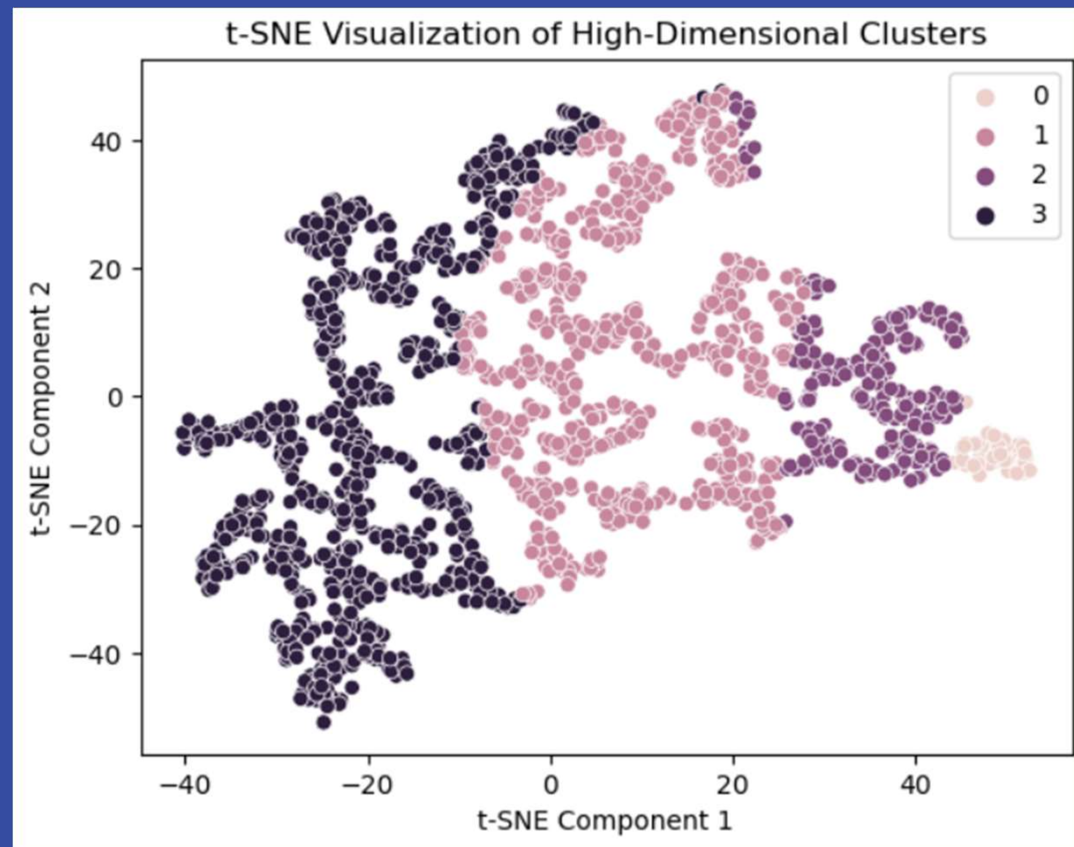


0	B11001_007E	0.341022	6 Es
1	B25133_002E	0.329319	1 Estimate!
2	B11001_008E	0.312600	7 Estimate!!Total:
3	B25132_005E	0.311248	4 Estimate!!
4	B11001_009E	0.308270	8 Estimate!!Tot
5	B08126_061E	0.234539	
6	B08006_015E	0.234539	
7	B08124_029E	0.234539	
8	B08301_019E	0.234539	
9	B08006_032E	0.217987	
10	B08122_017E	0.213197	
11	B08122_020E	0.203795	19 Estimate!!Tot
12	B25132_004E	0.188267	3 Estimate!
13	B08124_030E	0.172386	
14	B08303_003E	0.139835	
15	B08126_069E	0.127180	68 Estim
16	B08126_070E	0.102291	69 Es admi
17	B15003_025E	0.037847	
18	B05001_002E	0.036872	1 Estin
19	B08126_074E	0.014360	73 Estin
20	B08126_041E	0.013217	40 Est
21	B28011_003E	0.001944	2 Estin
22	B05003_014E	-0.048422	13
23	B25132_009E	-0.119232	8 Esti

Visualization of High-Dimensional Clusters

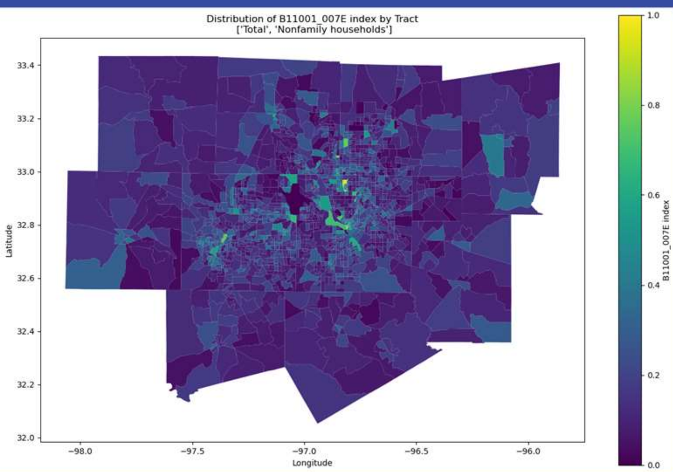
t-SNE (t-Distributed Stochastic Neighbor Embedding) is a machine learning algorithm used for data visualization and dimensionality reduction. It is particularly useful for visualizing high-dimensional data by transforming it into a low-dimensional space, typically two or three dimensions, while preserving the structure of the original data as much as possible.

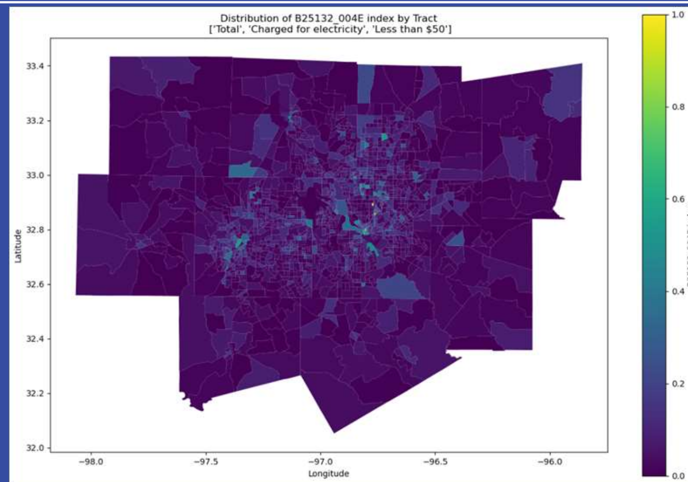


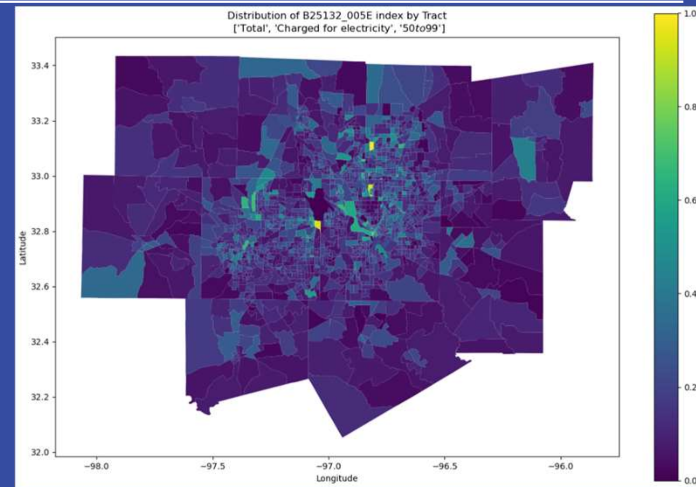


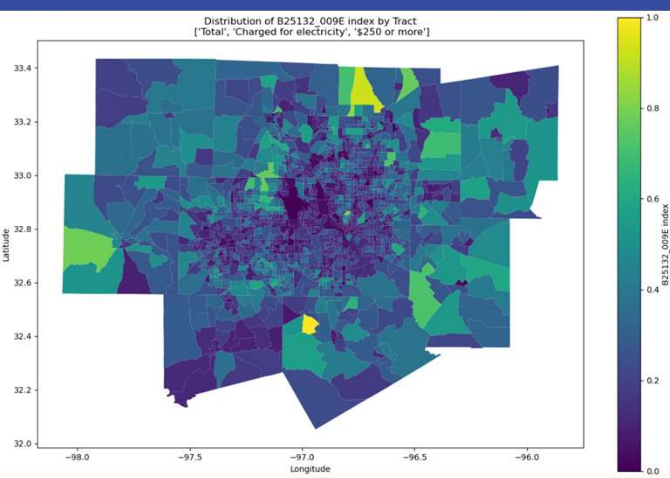
SMU

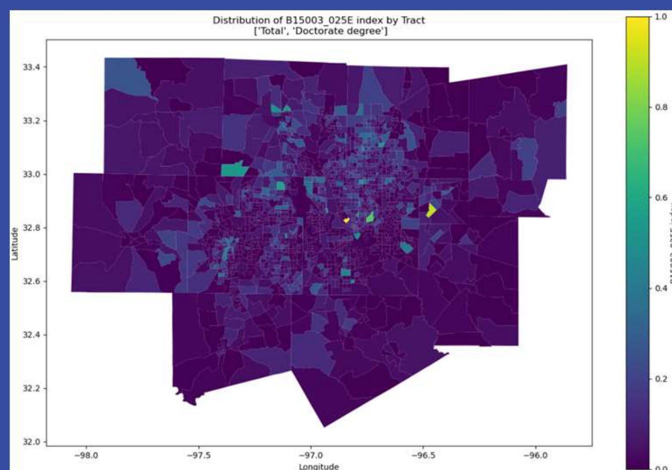
Spatial distribution of socioeconomic composition 1

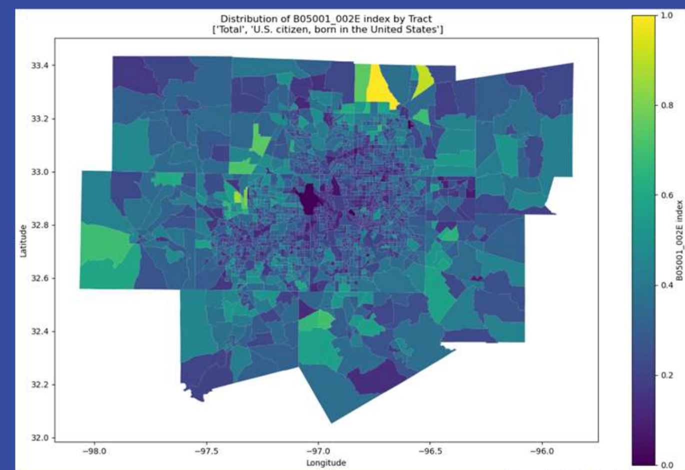


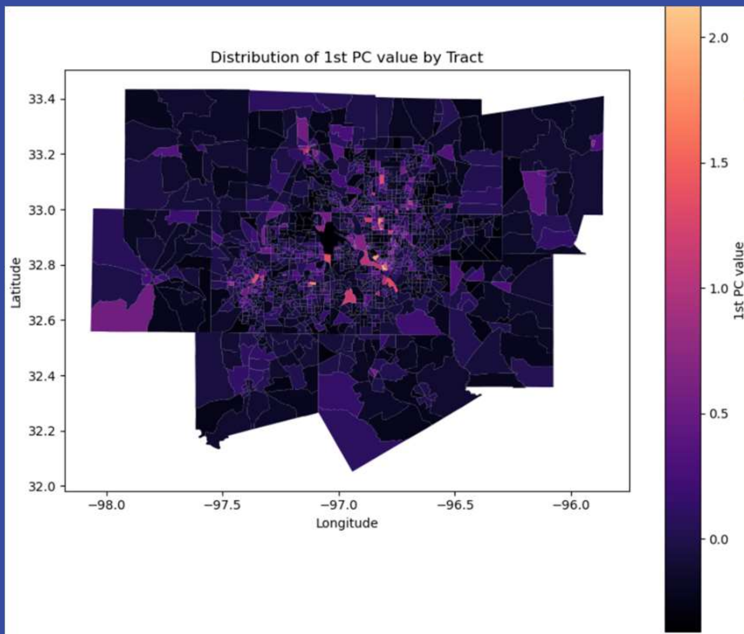


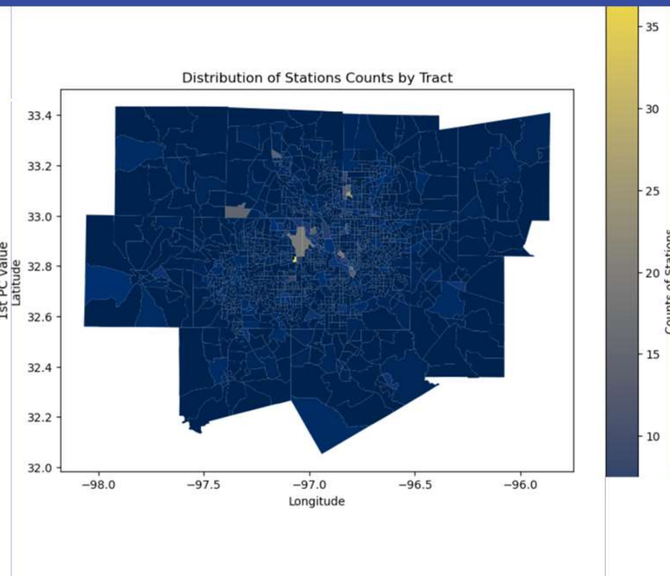


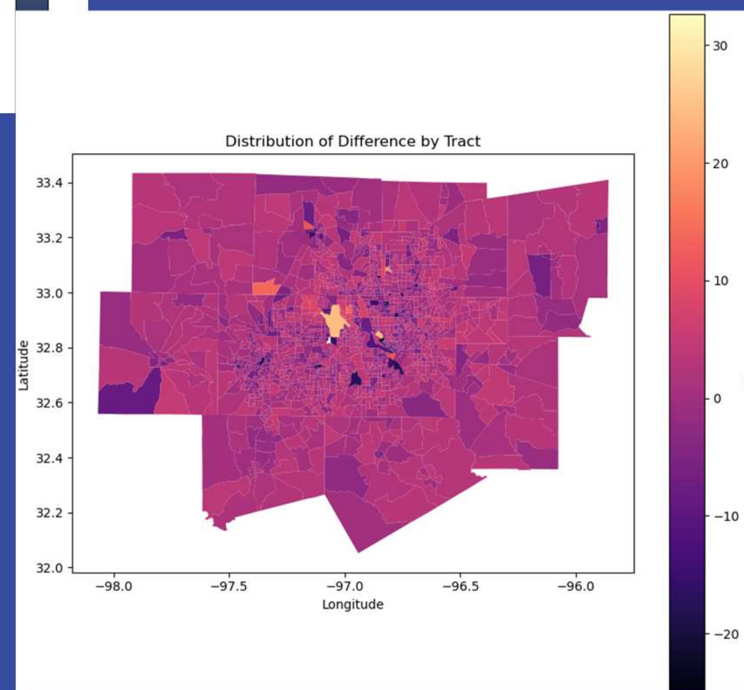












Quantifying Equity Level:

<u>EVCS Equity Index</u> = EVCS_index(counts) – alpha*PCA_PC1(var_1, var_2,….var_k)

Note:

EVCS_index = func(counts), active term: policymakers to take actions
PCA_PC1 = func(normalized features var_1,var_2, … var_k), passive term: changes as actions taken.
Alpha: an adjustable coefficient based on equity issues cared by local authorities
Normalized features are the most frequent and highest importance features selected from previous 5 algorithms

Quantifying spatial equity level:

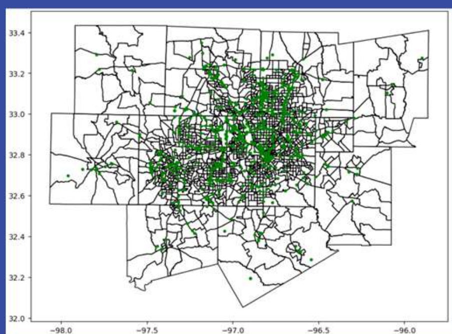
How to Quantify:

- Comparison between typologies pattern and EVCS placements;
- Develop **equity metrics**;
- Visualize the variations in equity level
- Develop RL-ABM to quantitatively analysis the equity

- Quantifying spatial equity levels for EVCS placements
- How EVCS placement densities varied spatially with existing socioeconomic inequalities.

Examining the equity

1. To propose a typology. Its pattern matches current EVCS quantities.
2. Understand the difference btw. Justice 40 and our typology
3. Quantifying spatial equity levels for EVCS placements



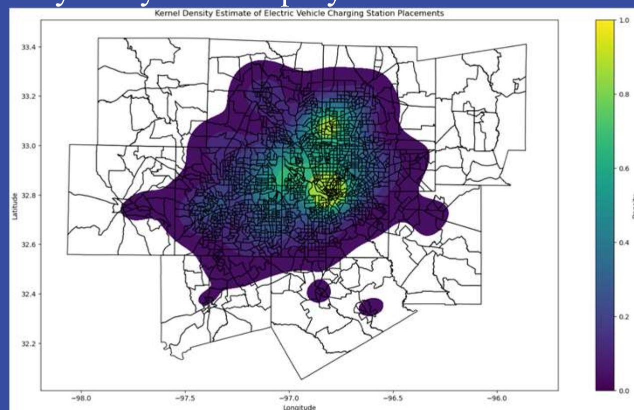
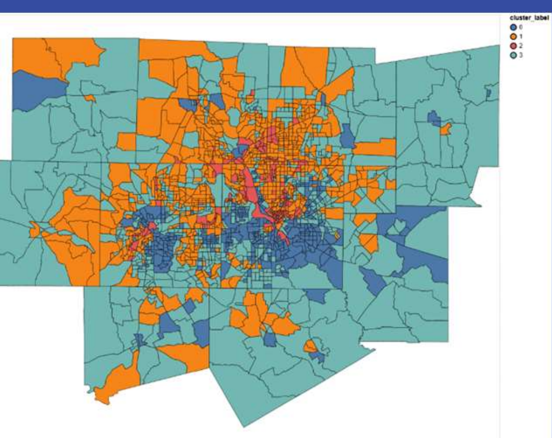
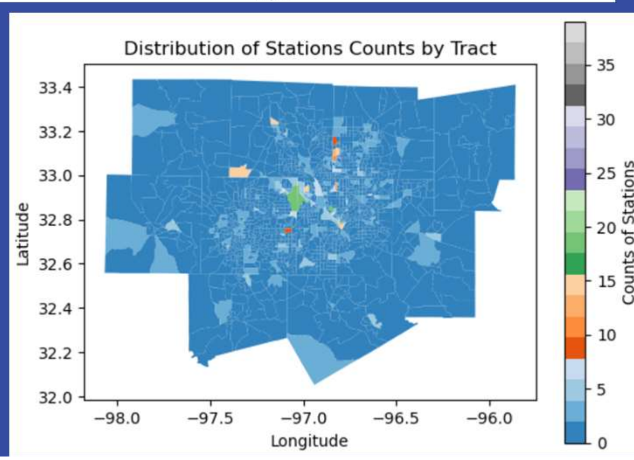
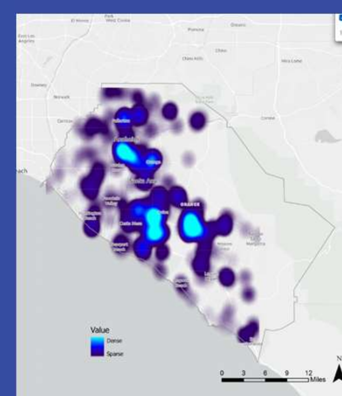


Table 4a
List of variables used to create equity indicators for Orange County.

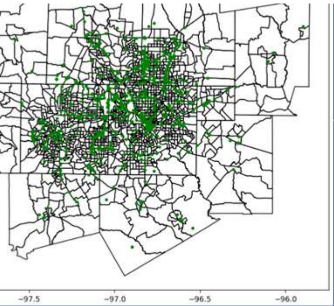
Variable	Description	Relevance
Vehicles Available	Average number of vehicles available in each household	Mobility indicator (Hanke et al., 2014, Luo et al., 2015, Javid & Nejat, 2017)
Population Density	Spatial distribution of population, calculated by total population/Land area	Demographic indicator (Plötz et al., 2014, Chakraborty, 2019)
Poverty	Percentage of population that lives under the poverty line	Socioeconomic indicator (Li, 2017, Hsu & Fingerman, 2021, Javid & Nejat, 2017)
Education	Percentage of population that holds a bachelor's degree or higher	Socioeconomic indicator (Hanke et al., 2014, Nayum et al., 2016, Javid & Nejat, 2017)
Income	Average median household income	Socioeconomic indicator (Hanke et al., 2014, Nayum et al., 2016)
Household Size	Average number of persons living in a household	Demographic indicator (Plötz et al., 2014, Chakraborty, 2019)
Housing Affordability	Percentage of population that spend more than 30% of monthly income on housing	Socioeconomic indicator (Westin et al., 2018, Hanke et al., 2014, Nayum et al., 2016)
Average Commute Time	Average one-way travel time to work	Mobility indicator (Luo et al., 2015, Javid & Nejat, 2017)
Age Between 25 to 45	Percentage of population that are between age 25 to 45	Demographic indicator (Westin, 2018, Chakraborty, 2019)
Employment Rate	Percentage of employment for population over age of 16	Socioeconomic indicator (Li, 2017, Hsu & Fingerman, 2021, Javid & Nejat, 2017)
Distance to EVCS	Distance between centroid of Census block group and the closest EVCS	Mobility indicator (Luo et al., 2015, Javid & Nejat, 2017)
PM 2.5 Level	Annual mean concentration particulate matter level	Environmental indicator ((Nayum, Klöckner and Mehmetoglu, 2016), Nordlund et al., 2016; Zeise & Blumenfeld, 2022)
Traffic Impact	Sum of traffic volumes (vehicle-kilometers per hour) divided by total road length (kilometers) within 150 meters of the census tract	Mobility and environmental indicator (Luo et al., 2015, Nordlund et al., 2016, Javid & Nejat, 2017)

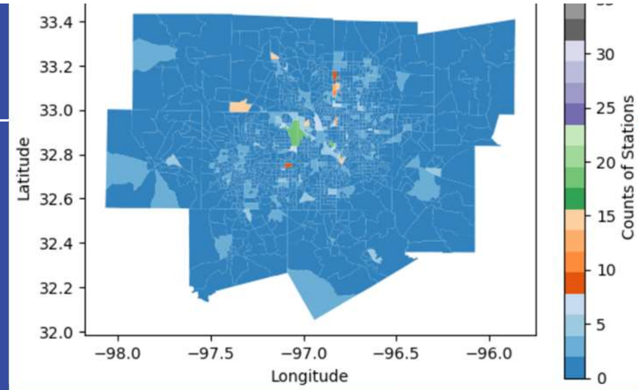




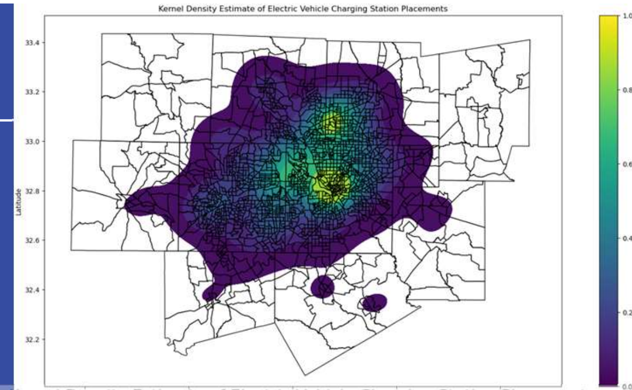


SMU

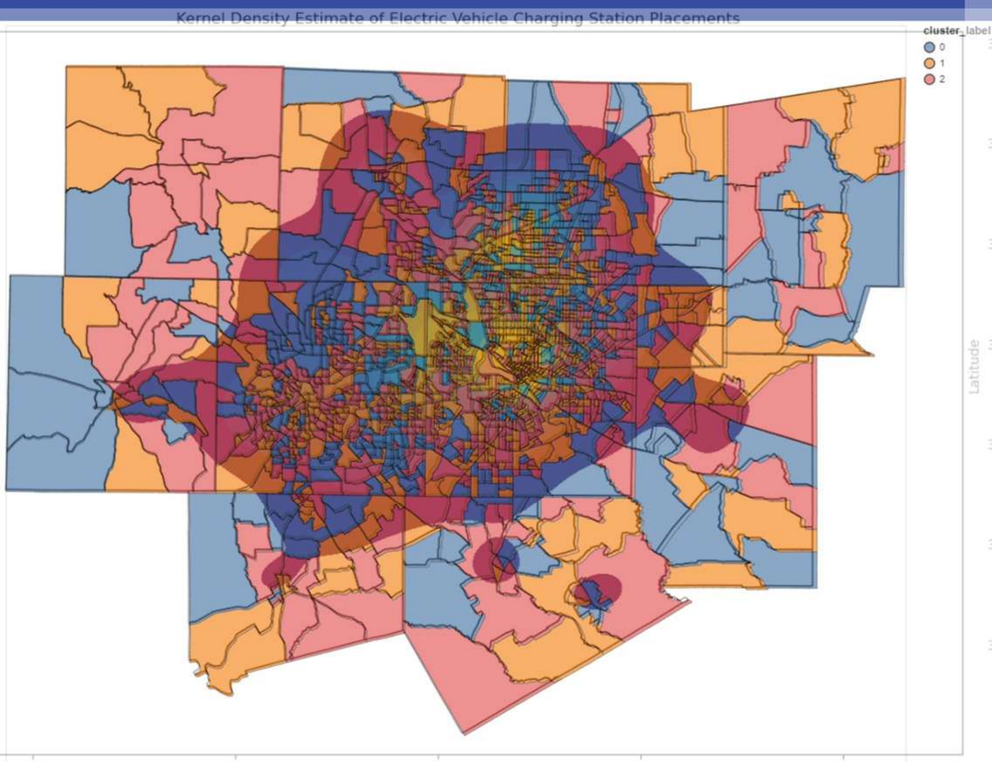




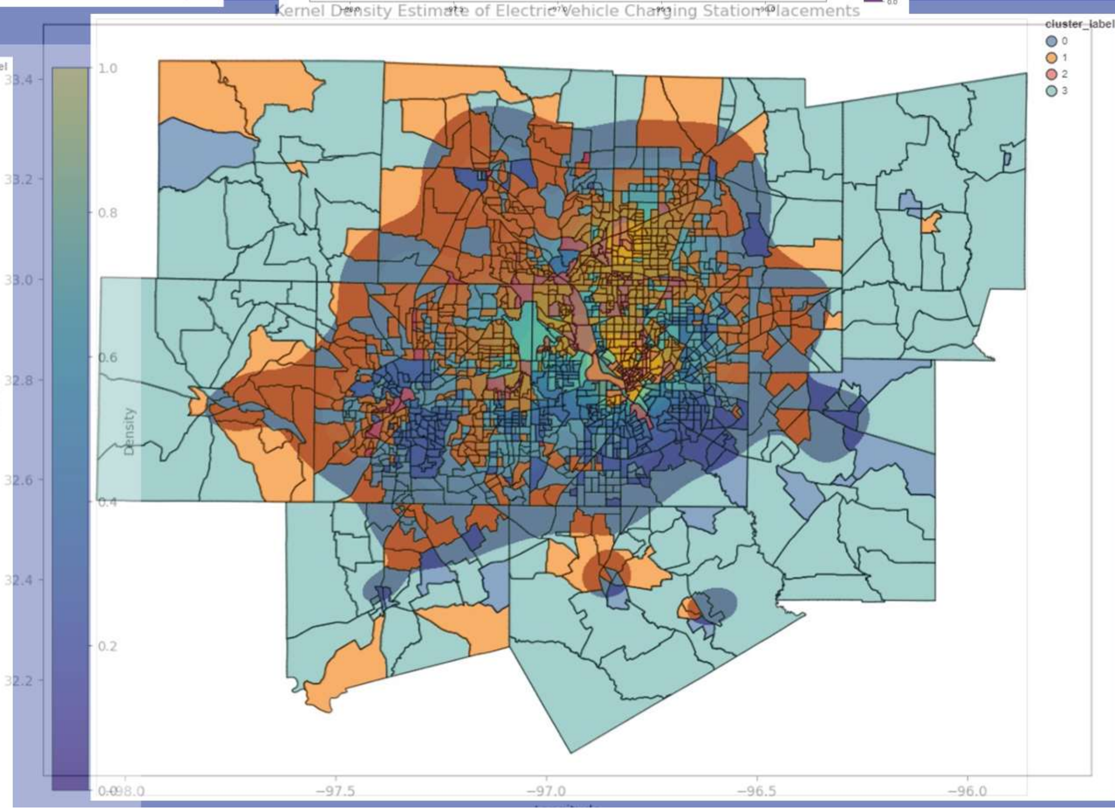
Latitude
Longitude
Counts of Stations



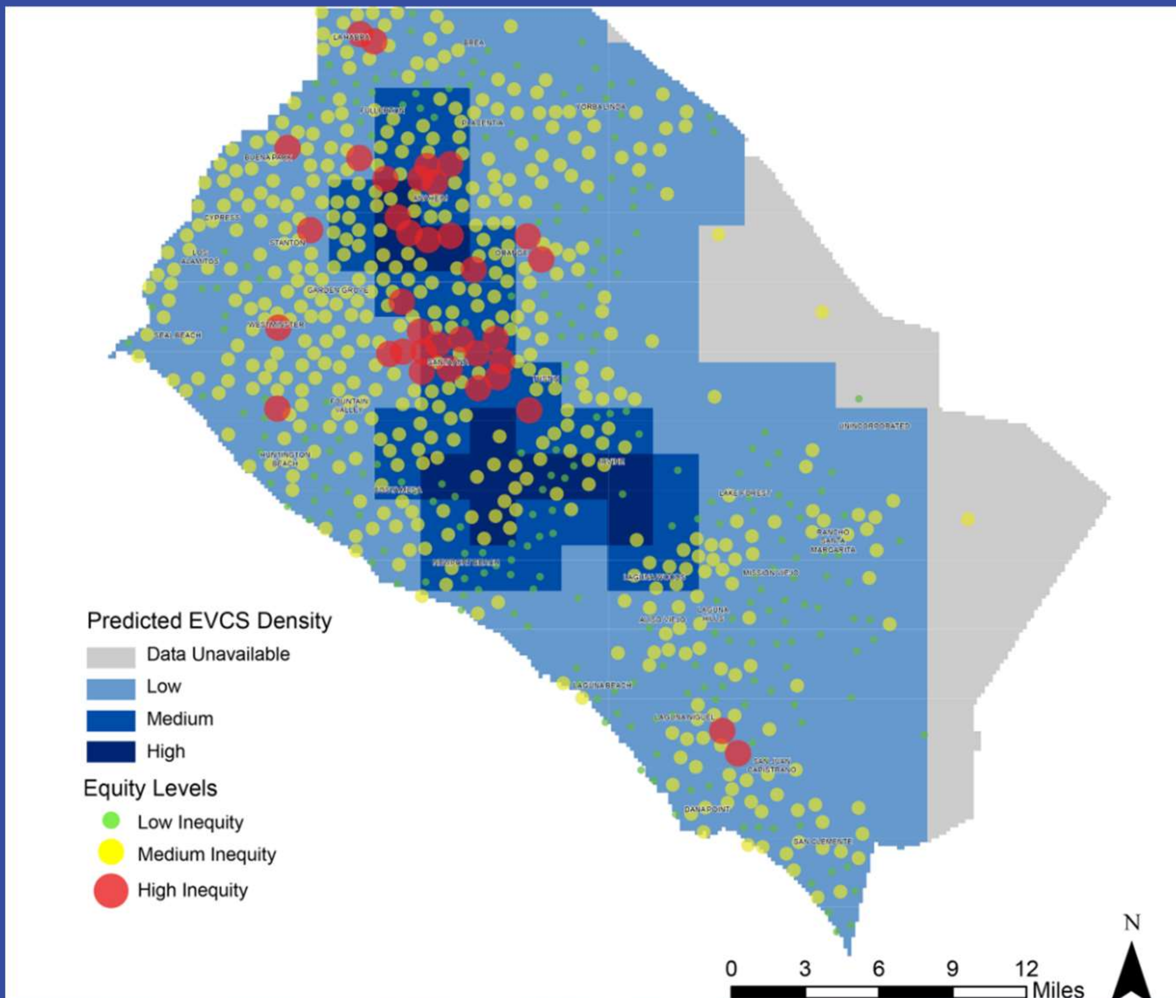
Kernel Density Estimate of Electric Vehicle Charging Station Placements
Latitude
Density



Kernel Density Estimate of Electric Vehicle Charging Station Placements
cluster_label
0
1
2



Kernel Density Estimate of Electric Vehicle Charging Station Placements
cluster_label
0
1
2
3
Density
Latitude



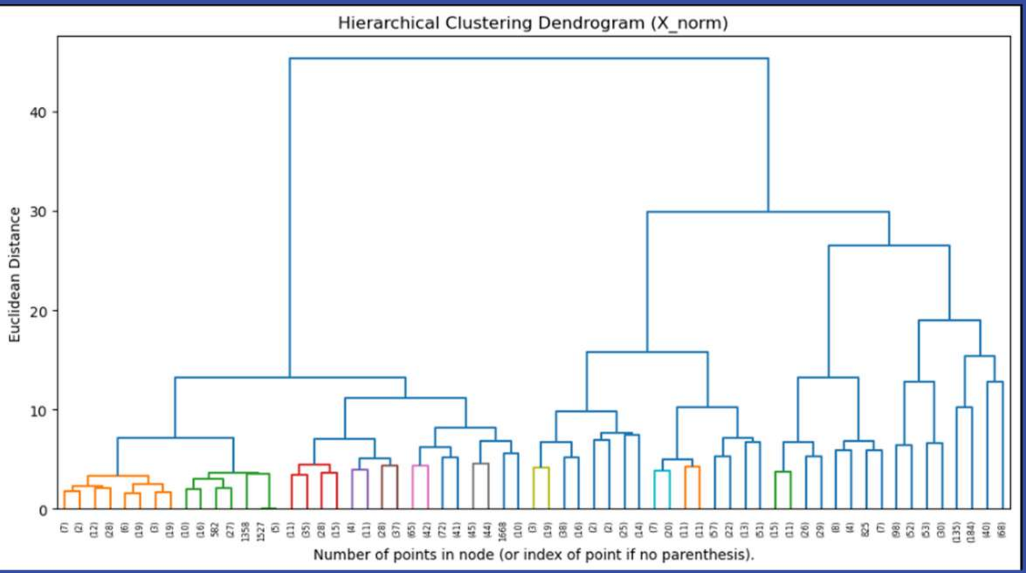
Predicted EVCS Density
Data Unavailable
Low
Medium
High
Equity Levels
Low Inequity
Medium Inequity
High Inequity
N
0 3 6 9 12
Miles

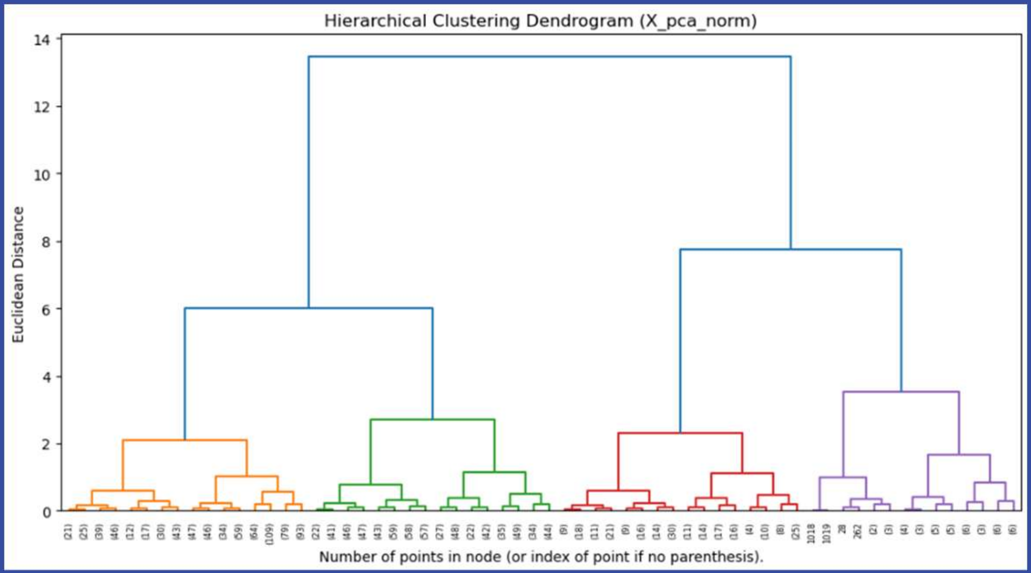
Comparison: dendrogram

» **NREL paper: Inequality and the future of electric mobility in 36 U.S. Cities: An innovative methodology and comparative assessment**

» **Proposed approach**

- feature extraction
- dimension reduction (PCA)





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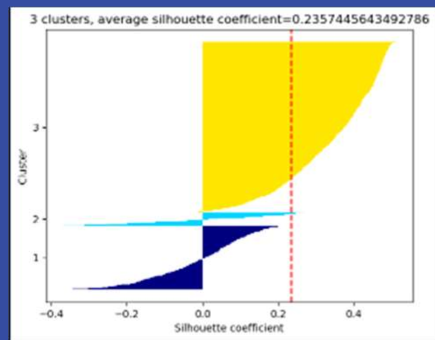
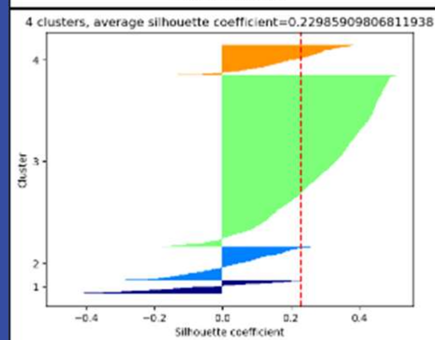
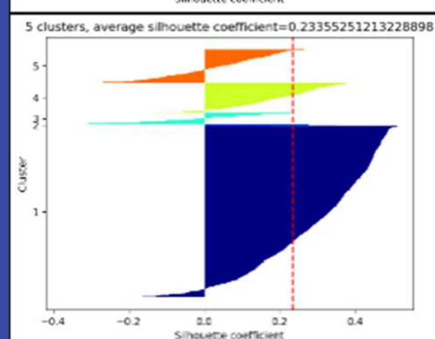
Comparison: Silhouette analysis

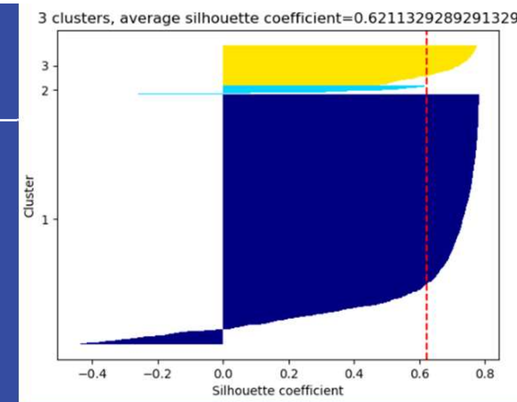
» **Inequality and the future of electric mobility in 36 U.S. Cities: An innovative methodology and comparative assessment**

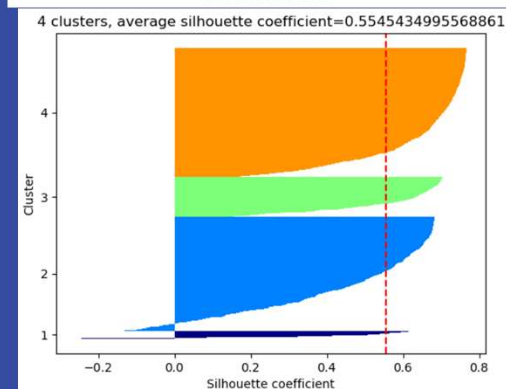


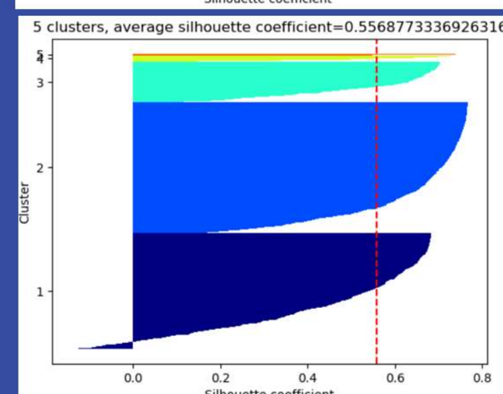




» **Proposed approach**

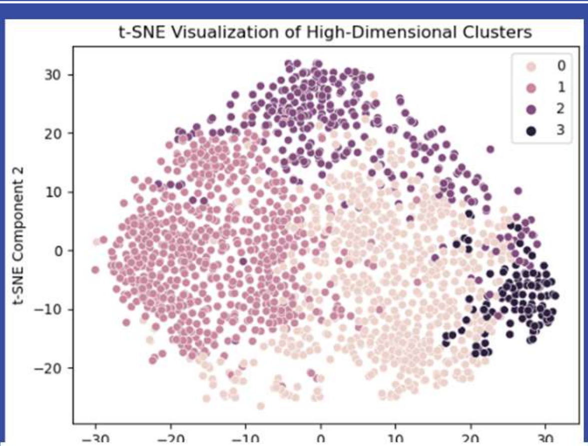


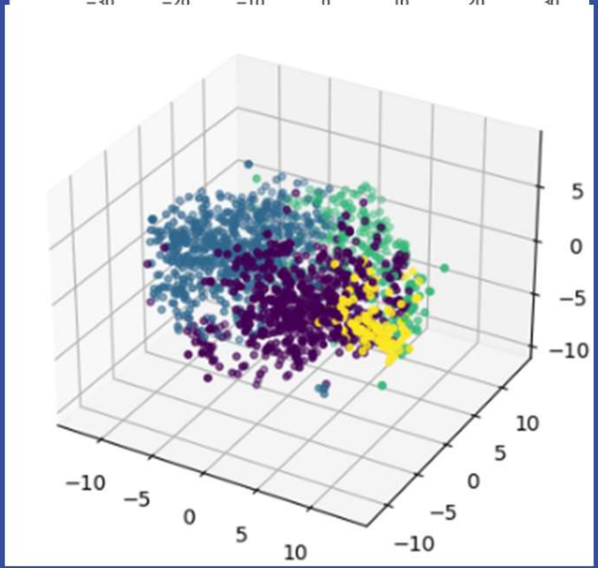




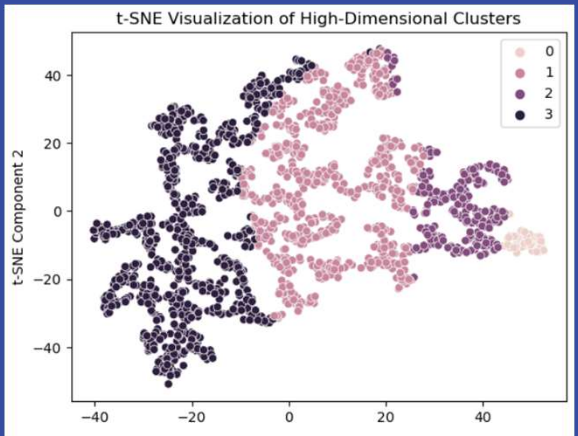
Comparison: cluster visualization

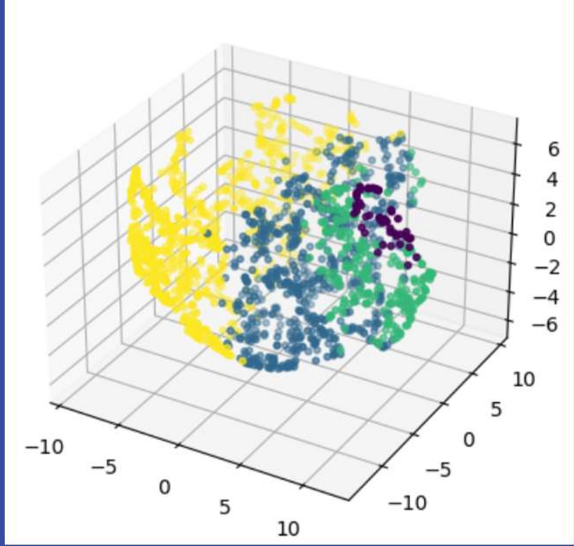
» **Inequality and the future of electric mobility in 36 U.S. Cities: An innovative methodology and comparative assessment**





» **Proposed approach**





Agent-Based Modeling vs Reinforcement Learning

Table 1. Comparison of Agent Based Modeling and Reinforcement Learning

Theory-driven Agent-Based Modeling	vs	Data-driven Reinforcement Learning
Agents' behavior generate a system behaviour		Focus on one agents' decision
Each step and parameter are interpretable, based on theories and laws		Uninterpretable, each parameter has no physical significance
Use factors that already known to influence social/physical/natural phenomenon		Capable of finding latent factors
Iteration always required (computationally expensive)		Iteration only required in the process of training (Faster in prediction)
Less data needed		Need significant large amount of data
Sensitive to missing data or attributes		Not sensitive to missing data or attributes
Model based		Model free
Deterministic and robust policies		Stochastic policy (Exploration and exploitation tradeoff)

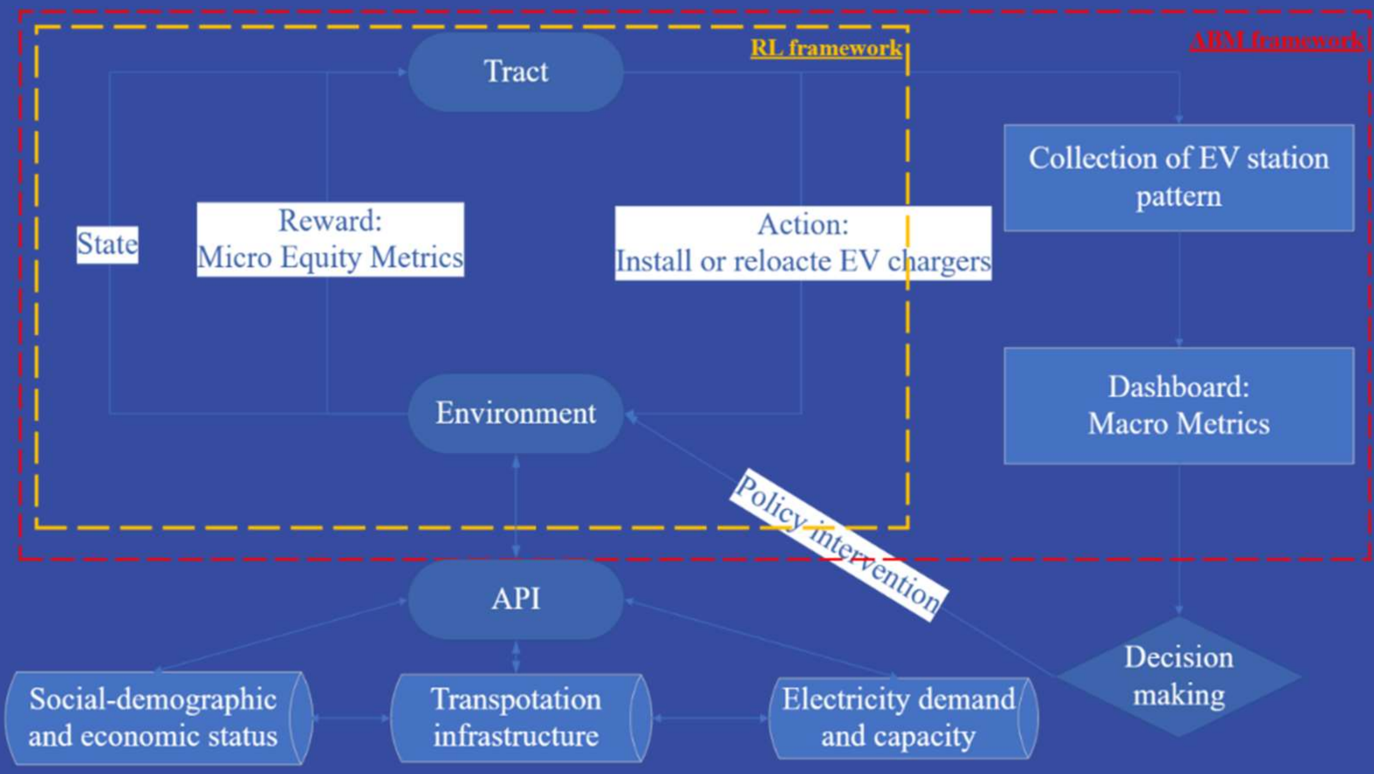
Hybrid modeling for Multi-agent system

Paradigm of agent based modeling for

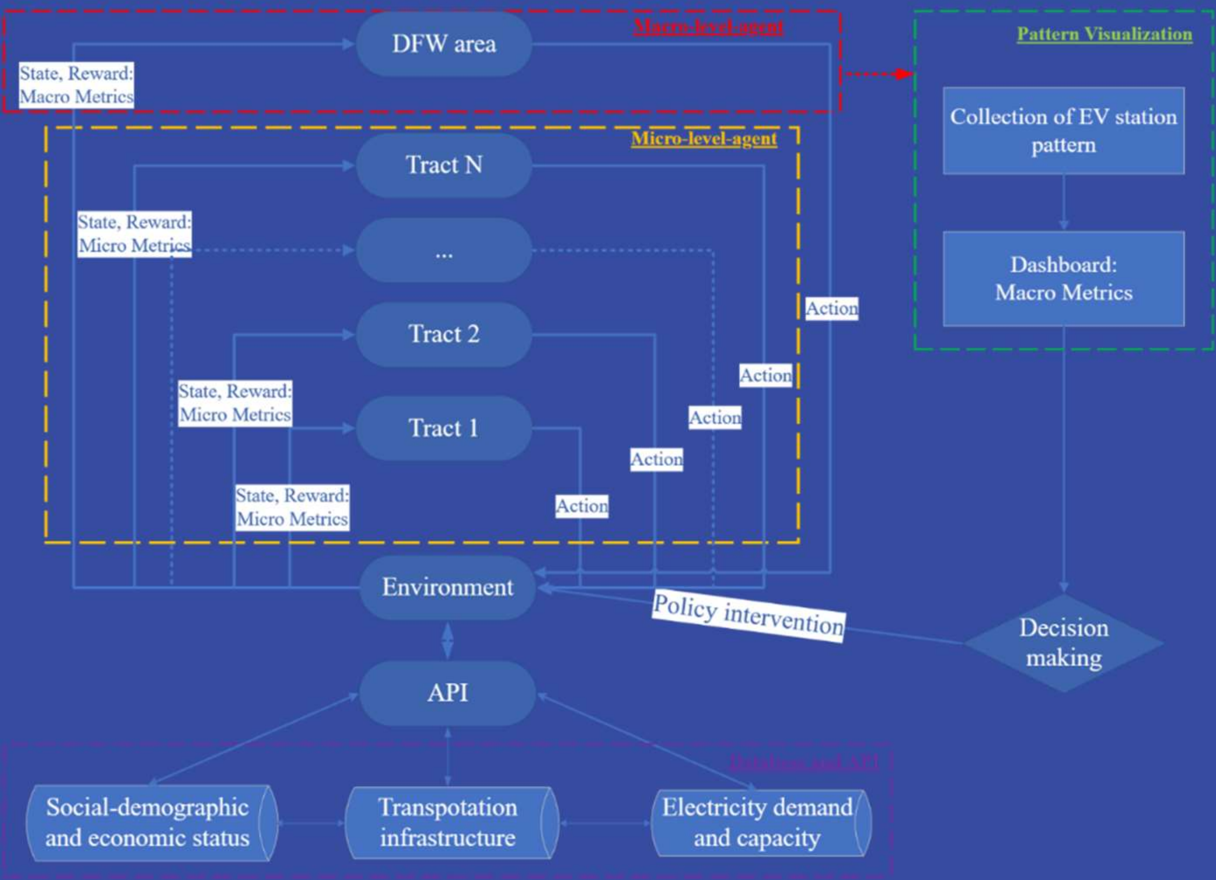
Reinforcement Learning

SMU

Single-RL-ABM framework



MARL-ABM



Multi-agent System:
MARL<=> ABM

- » Micro-level agent: Tracts
- » Macro-level agent: DFW
- » Goal: reach to a stable state
- » Mode: Cooperative/Competitive/Mixed

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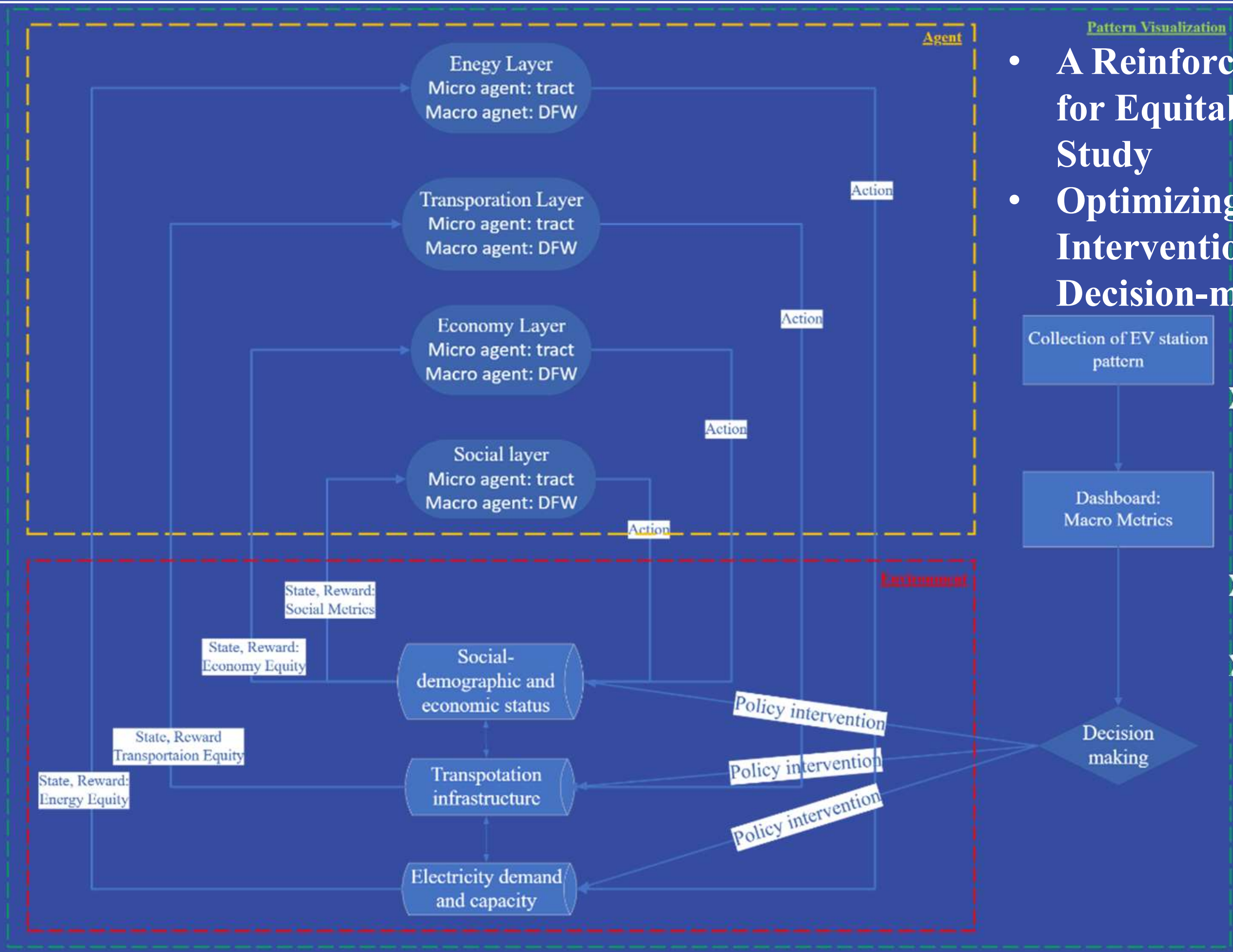
Multi-layer MARL-ABM



- **A Reinforcement Learning Driven Agent-Based Model for Equitable EV Charging Stations Deployment: A Case Study**
- **Optimizing Multi-Criteria Equity in Energy Policy Interventions: A Multi-Agent Reinforcement Learning Decision-making Framework with Case Study**

» Agents are Energy/Transportation/Economy sectors

» Decoupling reward design process

» Each sector can design their own reward/metrics

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multi-agent reinforcement learning (MARL)

» multi-agent reinforcement learning (MARL) is a cutting-edge and active area of research within the field of artificial intelligence and machine learning. MARL addresses the challenges of decision-making in environments where multiple agents interact and their actions impact each other's outcomes.

Communication among agents

- Fully Cooperative Communication: Agents collaborate to reach the same goal and optimize a common return. E.g. industrial robots => same goal, same reward

- Fully Competitive Communication: One agent’s gain is the other agent’s loss.
  - Sum-zero game: the sum of rewards is zero. One win means other ‘s lose. e.g fighting => winner’s reward = loser’s loss
  - Non Sum-zero: the sum of rewards is not zero. Predator-prey => lion vs deer => meal vs life=> lion’s rewards < deer’s loss

- Mixed Cooperative & Competitive communication: e.g. Soccer game=> teammates: cooperative | teams: competitive

- Self-interested mode: Agents are self-interested. They only want to maximize their own return. Their rewards may or may not conflict as they don’t care. E.g. trading system, autonomous vehicles

From the theoretical point of view, *game theory* has quite a developed foundation for Cooperative and Competitive modes.

MARL: State, Action, State Transition

State:

» There are *n* agents.

» • Let S be the state.

» • Let A^i be the i-th agent's action.

» • State transition:

• $$p(s'|s, a^1, \cdots, a^n) = \mathbb{P}(S' = s'|S = s, A^1 = a^1, \cdots, A^n = a^n)$$

» The next state, S', depends on all the agents' actions

MARL: Reward

» Let R^i be the *i*-th agent's reward.

» Fully cooperative:

$$R^1 = R^2 = \cdots = R^n$$

» Fully competitive:

$$R^1 \propto -R^2$$

• R^i is proportional to R^j

» R^i depends on A^i as well as all the other agents' actions A^j

» How to design rewards for mixed and self-interested?

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MARL: Return

- Let R_t^i be the **reward** received by the i-th agent at time t.
- **Return** (of the i-th agent):

$$U_t^i = R_t^i + R_{t+1}^i + R_{t+2}^i + R_{t+3}^i + \cdots$$

- **Discounted return** (of the i-th agent):

$$U_t^i = R_t^i + \gamma \cdot R_{t+1}^i + \gamma^2 \cdot R_{t+2}^i + \gamma^3 \cdot R_{t+3}^i + \cdots$$

Here, $\gamma \in [0, 1]$ is the discount rate.

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MARL: Policy

Policy Network

- Each agent has its own policy network: $\pi(a^i \mid s; \boldsymbol{\theta}^i)$.
- Policy networks can be exchangeable: $\boldsymbol{\theta}^1 = \boldsymbol{\theta}^2 = \cdots = \boldsymbol{\theta}^n$.
  - Self-driving cars can have the same policy.
- Policy networks can be nonexchangeable: $\boldsymbol{\theta}^i \neq \boldsymbol{\theta}^j$.
  - Soccer players have different roles, e.g., striker, defender, goalkeeper.

MARL: Uncertainty

Uncertainty in the Return

- The reward R_t^i depends on S_t and $A_t^1, A_t^2, \cdots, A_t^n$.
- Uncertainty in S_t is from the state transition, p.
- Uncertainty in A_t^i is from the policy network, $\pi(\cdot \mid s_t; \boldsymbol{\theta}^i)$.
- The return, $U_t^i = \sum_{k=0}^{\infty} \gamma^k \cdot R_{t+k}^i$, depends on:
  - all the future states: $\{S_t, S_{t+1}, S_{t+2}, \cdots\}$;
  - all the future actions: $\{A_t^i, A_{t+1}^i, A_{t+2}^i, \cdots\}$, for all $i = 1, \cdots, n$.

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MARL: State-Value Function

State-Value Function

- State-value of the i-th agent:

$$V^i(s_t; \boldsymbol{\theta}^1, \cdots, \boldsymbol{\theta}^n) = \mathbb{E}\left[U_t^i \mid S_t = s_t\right].$$

- The expectation is taken w.r.t. all the future actions and states except S_t.

- Randomness in actions: $A_t^j \sim \pi\left(\cdot \mid s_t; \boldsymbol{\theta}^j\right)$, for all $j = 1, \cdots, n$.
  (That is why the state-value V^i depends on $\boldsymbol{\theta}^1, \cdots, \boldsymbol{\theta}^n$.)

MARL: Convergence

Single-Agent Policy Learning

- Policy network: $\pi(a \mid s; \boldsymbol{\theta})$.
- State-value function: $V(s; \boldsymbol{\theta})$.
- $J(\boldsymbol{\theta}) = \mathbb{E}_S[V(S; \boldsymbol{\theta})]$ evaluates how good the policy is.
- Learn the policy network's parameter, $\boldsymbol{\theta}$, by

$$\max_{\boldsymbol{\theta}} J(\boldsymbol{\theta}).$$

- **Convergence:** $J(\boldsymbol{\theta})$ stops increasing.

Multi-Agent Policy Learning

Nash Equilibrium

- While all the other agents' policy remain the same, the i-th agent cannot get better expected return by changing its own policy.
- Every agent is playing a best-response to the other agents' policies.
- Nash equilibrium indicates convergence because no one has any incentive to deviate.

- Convergence: No agent can get better expected return by improving its own policy.
- If there is only one agent, convergence means the objective function does not increase any more.
- If there are multiple agents, **Nash equilibrium[]** means convergence.

SMU

MARL: Difficulty

» Simply using single agent algo to MARL, not convergence

$$V_\pi(s) = \mathbb{E}_A\Big[Q_\pi(s, A)\Big] = \sum_{a\in\mathcal{A}} \pi(A|s;\boldsymbol{\theta}) \cdot Q_\pi(s, a)$$

The i-th agent's policy network: $\pi\big(a^i \mid s; \boldsymbol{\theta}^i\big)$.

The i-th agent's state-value function: $V^i(s; \boldsymbol{\theta}^1, \cdots, \boldsymbol{\theta}^n)$.

Objective function: $J^i(\boldsymbol{\theta}^1, \cdots, \boldsymbol{\theta}^n) = \mathbb{E}_S\big[V^i(S; \boldsymbol{\theta}^1, \cdots, \boldsymbol{\theta}^n)\big]$.

Learn the policy network's parameter, $\boldsymbol{\theta}^i$, by

$$\max_{\boldsymbol{\theta}^i} J^i(\boldsymbol{\theta}^1, \cdots, \boldsymbol{\theta}^n).$$

$$\begin{aligned}
\boldsymbol{\theta}^1 &\leftarrow \boldsymbol{\theta}^1 + \alpha^1 \cdot \nabla_{\boldsymbol{\theta}^1} J(\boldsymbol{\theta}^1, \cdots, \boldsymbol{\theta}^m), \\
\boldsymbol{\theta}^2 &\leftarrow \boldsymbol{\theta}^2 + \alpha^2 \cdot \nabla_{\boldsymbol{\theta}^2} J(\boldsymbol{\theta}^1, \cdots, \boldsymbol{\theta}^m), \\
&\vdots \\
\boldsymbol{\theta}^m &\leftarrow \boldsymbol{\theta}^m + \alpha^m \cdot \nabla_{\boldsymbol{\theta}^m} J(\boldsymbol{\theta}^1, \cdots, \boldsymbol{\theta}^m).
\end{aligned}$$

» One agent's parameter changes will lead to variation of objective function of all agents

The i-th agent found $\boldsymbol{\theta}^i_\star = \underset{\boldsymbol{\theta}^i}{\operatorname{argmax}} J^i(\boldsymbol{\theta}^1, \cdots, \boldsymbol{\theta}^n)$

- » Meaning, if the agent finds the optimal parameter, once other agents change its policy, the agent has to find a new optimal parameter. This process will continue forever and can not converge

SMU

MARL summary

» Multi Agent System.

» • The agents are usually not independent.

  » • Every agent’s action can affect the next state.

  » • Thus, every agent can affect all the other agents.

» • Unless the agents are independent of each other, single-agent RL methods do not work well for MARL

SMU

Multi-agent Communication Architectures:

Centralized VS Decentralized

» **Fully decentralized**: Every agent uses its own observations and rewards to learn its policy. Agents do not communicate.

» **Fully centralized**: The agents send everything to the central controller. The controller makes decisions for all the agents.

» **Centralized training with decentralized execution**: A central controller is used during training. The controller is disabled after training

Partial Observations

» An agent may or may not have full knowledge of the state, S (globally)

» Partial observation: O^i != S

» Full observation: $O^1 = O^2 = \ldots. = O^i = S$

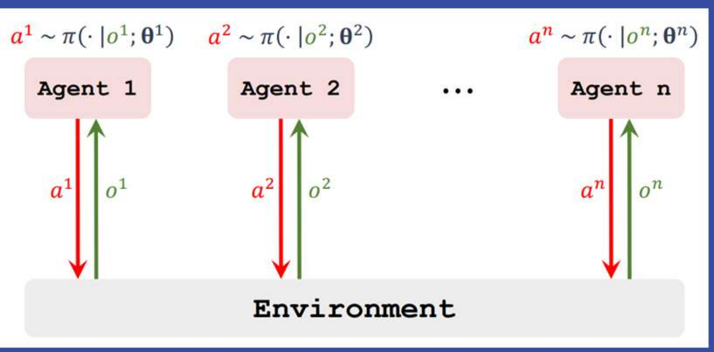
Multi-agent Communication Architectures:

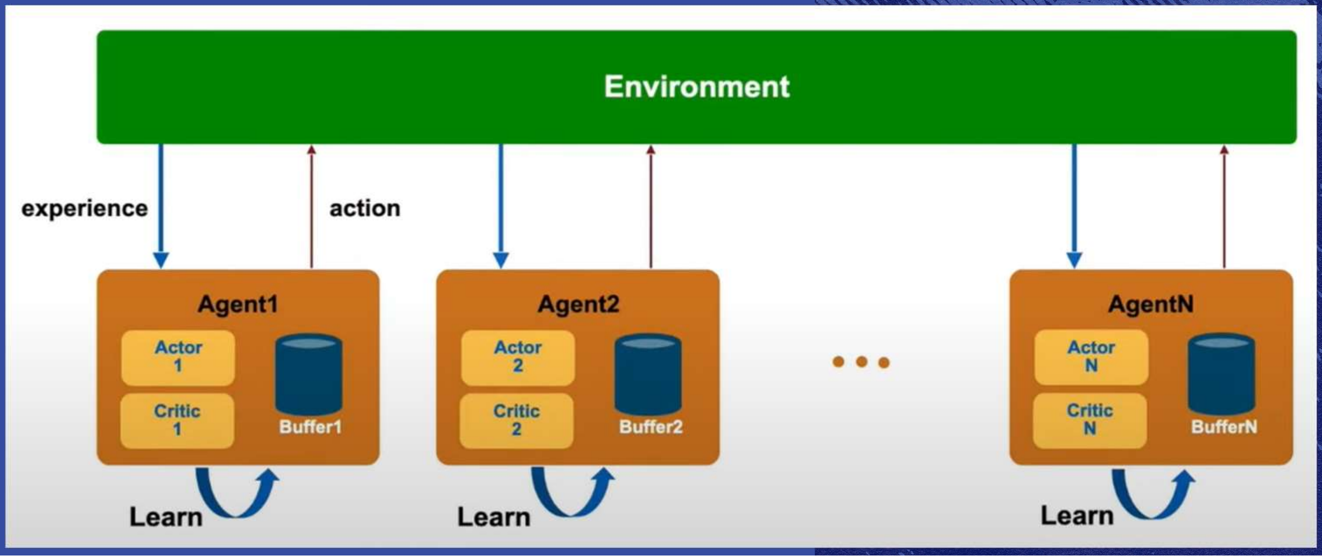
Fully decentralized: (in nature: single agent RL not MARL)

» Agents trained separately and learn its own policy network, no communication.

» After training, agents use its own policy network to make decision

» Shortcoming: Agents do not share observations and actions.(partial observation, non-stationary environment)





Multi-agent Communication Architectures:

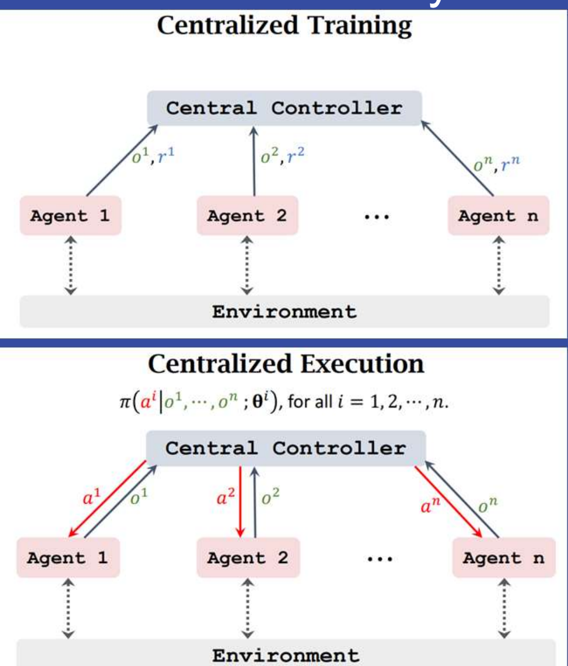
Fully Centralized:

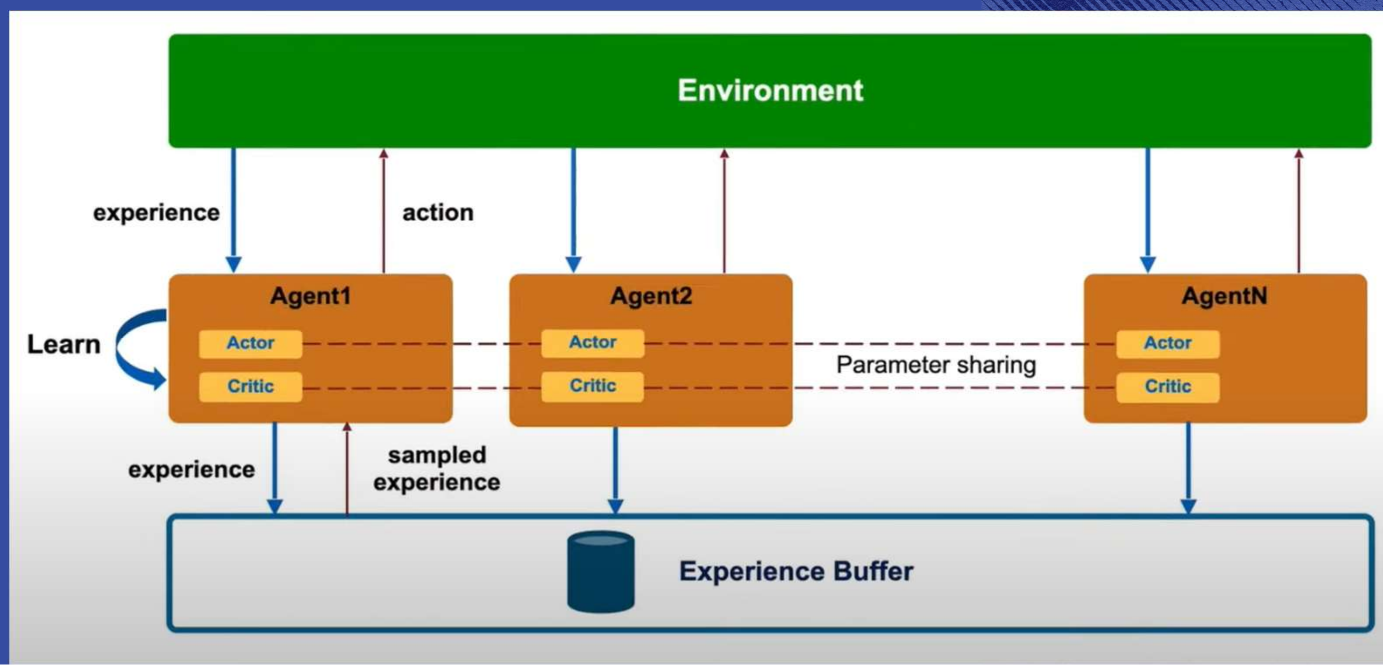
» Centralized Training: Training is performed by the controller.

» Centralized Execution: Decisions are made by the controller.

» Shortcoming: Slow during execution, Communication and synchronization cost time.

» Benefits: stationary environment since the entire MAS is treated as entity



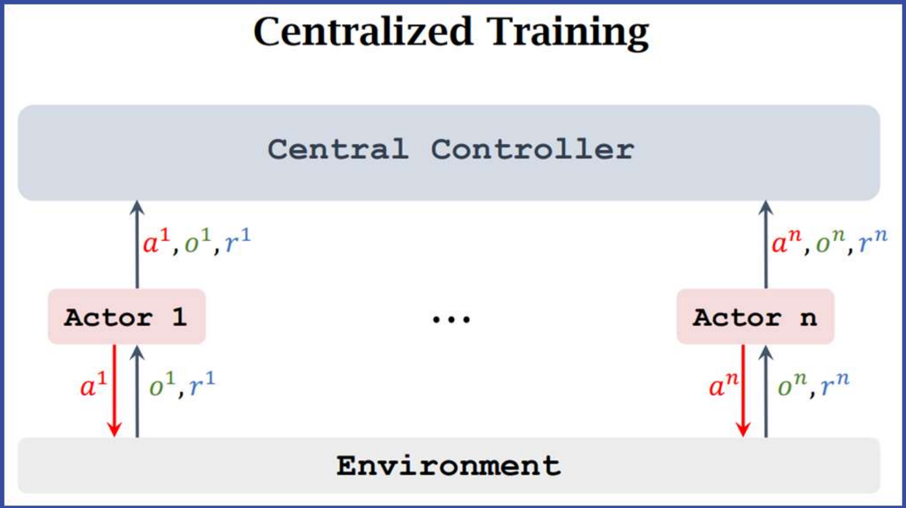


Multi-agent Communication Architectures:

Centralized Training with Decentralized Execution:

» Centralized Training: During training, the central controller knows all the agents' observations, actions, and rewards. Training Value Network.

» Decentralized Execution: During execution, the central controller and its value networks are not used. Agents use its own Policy Network.



Multi-agent Communication Architectures:

Parameter Sharing:

» Soccer game: each player has own function(different positions), no parameter sharing

» Autonomous Vehicles: agents are exchangeable, can share parameters

Policy networks: $\pi\left(a^i \middle| o^i ; \boldsymbol{\theta}^i\right)$, for $i = 1, 2, \cdots, n$.

Value networks: $q\left(\mathbf{o}, \mathbf{a} ; \mathbf{w}^i\right)$, for $i = 1, 2, \cdots, n$.

Trainable parameters: $\left\{\boldsymbol{\theta}^i, \mathbf{w}^i\right\}_{i=1}^{n}$

Parameter sharing: $\boldsymbol{\theta}^i = \boldsymbol{\theta}^j$ and $\mathbf{w}^i = \mathbf{w}^j$, for some i and j

Multi-agent Communication Architectures:

Summary:

» Soccer game: each player has own function(different positions), no parameter sharing

» Autonomous Vehicles: agents are exchangeable, can share parameters

	execution Policy (Actor)	training Value (Critic)
Fully Decentralized	$\pi(a^i \| o^i; \boldsymbol{\theta}^i)$	$q(o^i, a^i; \mathbf{w}^i)$
Fully Centralized	$\pi(a^i \| \mathbf{o}; \boldsymbol{\theta}^i)$	$q(\mathbf{o}, \mathbf{a}; \mathbf{w}^i)$
Centralized Training, Decentralized Execution	$\pi(a^i \| o^i; \boldsymbol{\theta}^i)$	$q(\mathbf{o}, \mathbf{a}; \mathbf{w}^i)$

SMU

Algorithms

» **Independent Learning (IL)**
For IL, each agent is learning independently and perceives the other agents as part of the environment.

» **IQL:** In Independent Q-Learning (IQL) [Tan, 1993], each agent has a decentralised state-action value function that is conditioned only on the local history of observations and actions of each agent. Each agent receives its local history of observations and updates the parameters of the Q-value network [Mnih et al., 2015] by minimising the standard Q-learning loss [Watkins and Dayan, 1992].

» **IA2C:** Independent synchronous Advantage Actor-Critic (IA2C) is a variant of the commonly-used **A2C** algorithm [Mnih et al., 2016, Dhariwal et al., 2017] for decentralised training in multi-agent systems. Each agent has its own actor to approximate the policy and critic network to approximate the value-function. Both actor and critic are trained, conditioned on the history of local observations, actions and rewards the agent perceives, to minimise the A2C loss.

» **IPPO:** Independent Proximal Policy Optimisation (IPPO) is a variant of the commonly-used PPO algorithm [Schulman et al., 2017] for decentralised training in multi-agent systems. The architecture of IPPO is identical to IA2C. The main difference between PPO and A2C is that PPO uses a surrogate objective which constrains the relative change of the policy at each update, allowing for more update epochs using the same batch of trajectories. In contrast to PPO, A2C can only perform one update epoch per batch of trajectories to ensure that the training batch remains on-policy

Algorithms

» **Centralised Training Decentralised Execution (CTDE)**

In contrast to IL, CTDE allows sharing of information during training, while policies are only conditioned on the agents' local observations enabling decentralised execution.

Centralised policy gradient methods One category of CTDE algorithms are centralised policy gradient methods in which each agent consists of a decentralised actor and a centralised critic, which is optimised based on shared information between the agents.

MADDPG: Multi-Agent DDPG (MADDPG) [Lowe et al., 2017] is a variation of the DDPG algorithm [Lillicrap et al., 2015] for MARL. The actor is conditioned on the history of local observations, while critic is trained on the joint observation and action to approximate the joint state-action value function. Each agent individually minimises the deterministic policy gradient loss [Silver et al., 2014]. A common assumption of DDPG (and thus MADDPG) is differentiability of actions with respect to the parameters of the actor, so the action space must be continuous. Lowe et al. [2017] apply the Gumbel-Softmax trick [Jang et al., 2017, Maddison et al., 2017] to learn in discrete action spaces.

COMA: In Counterfactual Multi-Agent (COMA) Policy Gradient, Foerster et al. [2018] propose a modification of the advantage in the actor's loss computation to perform counterfactual reasoning for credit assignment in cooperative MARL. The advantage is defined as the discrepancy between the state-action value of the followed joint action and a counterfactual baseline. The latter is given by the expected value of each agent following its current policy while the actions of other agents are fixed. The standard policy loss with this modified advantage is used to train the actor and the critic is trained using the TD-lambda algorithm [Sutton, 1988].

MAA2C: Multi-Agent A2C (MAA2C) is an actor-critic algorithm in which the critic learns a joint state value function (in contrast, the critics in MADDPG and COMA are also conditioned on actions). It extends the existing on-policy actor-critic algorithm A2C by applying centralised critics conditioned on the state of the environment rather than the individual history of observations. It is often used as a baseline in MARL research and is sometimes referred to as Central-V, because it computes a centralised state value function. However, MAPPO also computes a centralised state value function, and in order to avoid confusion we refer to this algorithm as MAA2C.

MAPPO: Multi-Agent PPO (MAPPO) [Yu et al., 2021] is an actor-critic algorithm (extension of IPPO) in which the critic learns a joint state value function, similarly to MAA2C. In contrast to MAA2C, which can only perform one update epoch per training batch, MAPPO can utilise the same training batch of trajectories to perform several update epochs.

Value Decomposition Another recent CTDE research direction is the decomposition of the joint state-action value function into individual state-action value functions.

VDN: Value Decomposition Networks (VDN) [Sunehag et al., 2018] aim to learn a linear decomposition of the joint Q-value. Each agent maintains a network to approximate its own state-action values. VDN decomposes the joint Q-value into the sum of individual Q-values. The joint state-action value function is trained using the standard DQN algorithm [Watkins and Dayan, 1992, Mnih et al., 2015]. During training, gradients of the joint TD loss flow backwards to the network of each agent.

QMIX: QMIX [Rashid et al., 2018] extends VDN to address a broader class of environments. To represent a more complex decomposition, a parameterised mixing network is introduced to compute the joint Q-value based on each agent's individual state-action value function. A requirement of the mixing function is that the optimal joint action, which maximises the joint Q-value, is the same as the combination of the individual actions maximising the Q-values of each agent. QMIX is trained to minimise the DQN loss and the gradient is backpropagated to the individual Q-values.

Experiment Design

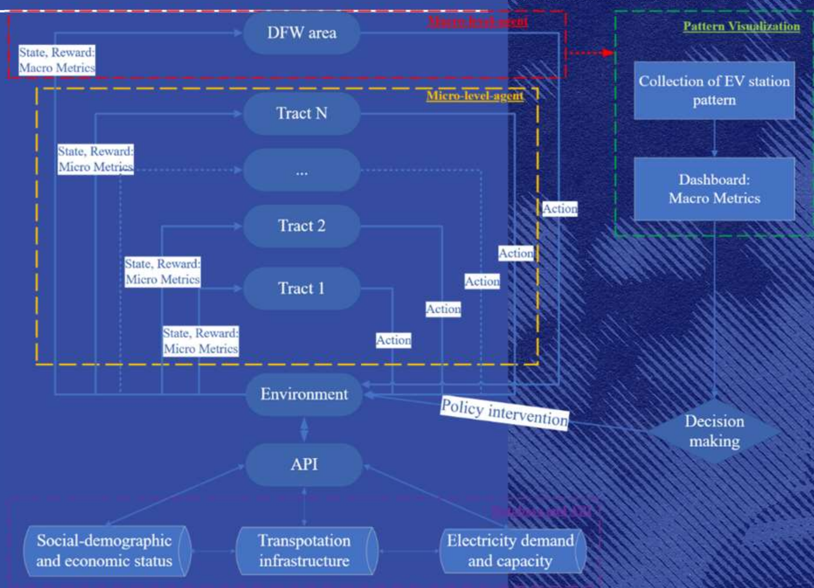
What factors determine the optimal policy?

It can be clearly seen from the BOE

$$v(s) = \max_{\pi} \sum_{a} \pi(a|s) \left(\sum_{r} p(r|s,a) r + \gamma \sum_{s'} p(s'|s,a) v(s') \right)$$

that there are three factors:

- Reward design: r
- System model: $p(s'|s,a)$, $p(r|s,a)$
- Discount rate: γ
- $v(s), v(s'), \pi(a|s)$ are unknowns to be calculated



- » Env design
  - » Input: actions,
  - » Interaction with current state, described via selected features/attributes
  - » Output: rewards and next states
- » Action design
  - » For example: build more EVCS, people move among tracts, decrease electricity price, etc.
- » Reward design
  - » Unified multi-criteria equity metrics

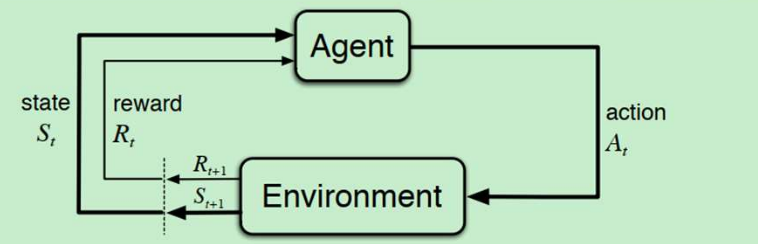


Figure 3.1: The agent–environment interaction in a Markov decision process.

Env design

» What does the env include?

- » Completed State: all dataset -> cluster modelling-> dimension reduction -> selected features
- » Transformed State : selected features
- » Action: (electricity, transportation, economy, social-demographic) | (macro-level action, micro level action)
- » Reward: associated to equity metrics,

```python
from gym import Env
from gym.spaces import Discrete, Box
import numpy as np
import random

class Multiagent_Env(Env):
    def __init__(self, n_chargers= random.randint(0,10), population = 200000, monthly_electricity_cost =100, car_counts=3, household_income=5000):
        # Actions we can take, (0: +1, 1: 0, 2: -1)
        self.action_space = Discrete(3)
        # n_chargers array: state is the number of chargers, population, monthly_electricity_cost, car_counts, household_income
        self.observation_space = Box(low=np.array([0],dtype=int), high=np.array([10000000], dtype=int), shape=(5,) dtype=int)
        # Set inital n_chargers
        self.state = n_chargers
        # inputs from our dataset
        # demographic
        self.population = population
        # electricity
        self.monthly_electricity_cost = monthly_electricity_cost
        # transportation
        self.car_counts = car_counts
        # Economic
        self.household_income = household_income
        # set episode length:
        self.maxlen = 100000

    def step(self, action):
        # Apply action
        self.state[0] += action

        # Design reward per equity/resilience/adoption metrics:
        # for testing purpose here, we apply a simple reward in terms of population-stations ratio
        # multiple level reward
        # population would move in or out based on ratio_pop_chg:
        ratio_pop_chg = round(self.population/(self.state+1))
        metrics = [900,1000] # we want the ratio to be 500-1000
        metrics_prime = [_ for _ in range(round(0.9*metrics[0]),metrics[0])]+[_ for _ in range(metrics[1], round(1.1*metrics[1]))]
        if ratio_pop_chg in range(*metrics):
            self.population += 0
            reward = 2
        elif ratio_pop_chg in metrics_prime:
            self.population += 100
            reward = 1
        # elif ratio_pop_chg in [_ for _ in range(10)]:
        #     self.population -= 10000
        #     reward = -2
        else:
            self.population -= 1000
            reward = -1


        # Check if time is done
        self.maxlen -=1
        if self.state ==0:
            isTerminated =True
        elif self.maxlen <= 0 or self.population <=0:
            isTerminated = True
        else:
```

Reward design

Compared to ABM, RL allows policymaker/stakeholders to focus on what they want. The framework will learn the policy for them

» State is the number of EV station within the tract

» R(s, a, s'): reward is function of state and action, it is associated with equity metrics.

» There is no equity metrics? Need to examine the disparities of EV charging station placements, and propose multi-criteria equity metrics

Proposed Future Research

- EVI-Equity is currently focused on distributional equity ("equitable access to all"). Other important equity aspects/dimensions (e.g., economics of charging infrastructure) could be considered.
- Incorporate NREL's EVI-Pro (daily short-distance), EVI-RoadTrip (long-distance road trips), and EVI-OnDemand (ride-hailing) for a more comprehensive and accurate EV charging infrastructure analysis for future years
- Expand the scope beyond light-duty vehicles, including medium- and heavy-duty vehicles (e.g., electric para-transit vehicles, school buses, transit buses)
- Create an interactive online platform so that users can evaluate equitable distribution of PEVs and EVSEs in their target geographical areas and download the underlying data and simulation results
- More holistic (i.e., system-of-systems) equity analysis by integrating EVI-Equity with buildings and/or electric grid simulation tools/models

Any proposed future work is subject to change based on funding levels.

NREL | 13

A. Roy and M. Law

Table 4a
List of variables used to create equity indicators for Orange County.

Variable	Description	Relevance
Vehicles Available	Average number of vehicles available in each household	Mobility indicator (Hanke et al., 2014, Luo et al., 2015, Javid & Nejat, 2017)
Population Density	Spatial distribution of population, calculated by total population/Land area	Demographic indicator (Plötz et al., 2014, Chakraborty, 2019)
Poverty	Percentage of population that lives under the poverty line	Socioeconomic indicator (Li, 2017, Hsu & Fingerman, 2021, Javid & Nejat, 2017)
Education	Percentage of population that holds a bachelor's degree or higher	Socioeconomic indicator (Hanke et al., 2014, Nayum et al., 2016, Javid & Nejat, 2017)
Income	Average median household income	Socioeconomic indicator (Hanke et al., 2014, Nayum et al., 2016)
Household Size	Average number of persons living in a household	Demographic indicator (Plötz et al., 2014, Chakraborty, 2019)
Housing Affordability	Percentage of population that spend more than 30% of monthly income on housing	Socioeconomic indicator (Westin et al., 2018, Hanke et al., 2014, Nayum et al., 2016)
Average Commute Time	Average one-way travel time to work	Mobility indicator (Luo et al., 2015, Javid & Nejat, 2017)
Age Between 25 to 45	Percentage of population that are between age 25 to 45	Demographic indicator (Westin, 2018, Chakraborty, 2019)
Employment Rate	Percentage of employment for population over age of 16	Socioeconomic indicator (Li, 2017, Hsu & Fingerman, 2021, Javid & Nejat, 2017)
Distance to EVCS	Distance between centroid of Census block group and the closest EVCS	Mobility indicator (Luo et al., 2015, Javid & Nejat, 2017)
PM 2.5 Level	Annual mean concentration particulate matter level	Environmental indicator ((Nayum, Klöckner and Mehmetoglu, 2016), Nordlund et al., 2016; Zeise & Blumenfeld, 2022)
Traffic Impact	Sum of traffic volumes (vehicle-kilometers per hour) divided by total road length (kilometers) within 150 meters of the census tract	Mobility and environmental indicator (Luo et al., 2015, Nordlund et al., 2016, Javid & Nejat, 2017)

Unified multi-criteria equity metrics

Explore

» Gain higher rewards if Increase the number of public EVCS in tracts with a higher percentage of “people-of-color” . R(S,a)

» Gain higher rewards if decrease the electricity price in tracts with a higher percentage of low-income tract

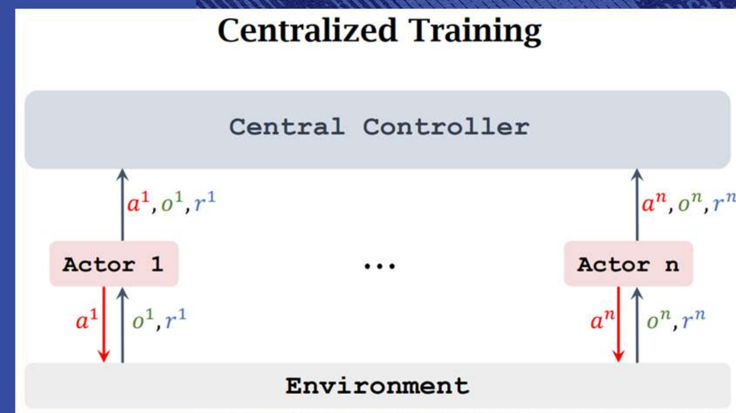
» Gain negative rewards if wealth tract get low electricity price.

» So on

EVCS Equity Index = EVCS_index(counts) – alpha*PCA_PC1(var_1, var_2,….var_k)

EVCS Equity Index (EVCSEI): Unified multi-criteria equity metrics

- Micro level agent: Tract EVCSEI,
  - Local agent:
  - Only have partial observation
  - Make decision independently, using policy network via centralized training
- Macro level agent: DFW EVCSEI,
  - Central controller:
  - Collect all information from agents (observation, reward, action)
  - Train agent based on collected information



Reward design

Reward is a function of state, next_state, action.

State is (n_chargers, population, monthly_electricity_cost, vehicle_occupancy, household_income, etc)

Initial Assumptions:

» Social-demographic: more EVCS with more population

» Electricity: more EVCS in low electricity tract

» Transportation: more EVCS with more EV

» Economic: more EVCS in more developed tract | More income

Multi-agent System:
MARL<=> ABM

Carefully design reward in order to find and understanding the trend

SMU

Actions design

» Micro agents(tracts):

- » build more EVCS in the tract
- » Attract people migrate from nearby tracts
- » decrease local electricity price
- » etc.

» Macro agent(DFW):

- » limit the expense for building more EVCS=>limit total number of EVCS
- » encourage resident migration to reach EVCS equity
- » etc.

MARL difficulties

» Simply using single agent algo to MARL, not convergence

$$V_\pi(s) = \mathbb{E}_A\left[Q_\pi(s,A)\right] = \sum_{a\in A}\pi(A|s;\boldsymbol{\theta})\cdot Q_\pi(s,a)$$

The i-th agent's policy network: $\pi\left(a^i \mid s; \boldsymbol{\theta}^i\right)$.

The i-th agent's state-value function: $V^i(s; \boldsymbol{\theta}^1, \cdots, \boldsymbol{\theta}^n)$.

Objective function: $J^i(\boldsymbol{\theta}^1, \cdots, \boldsymbol{\theta}^n) = \mathbb{E}_S\left[V^i(S; \boldsymbol{\theta}^1, \cdots, \boldsymbol{\theta}^n)\right]$.

Learn the policy network's parameter, $\boldsymbol{\theta}^i$, by

$$\max_{\boldsymbol{\theta}^i} J^i(\boldsymbol{\theta}^1, \cdots, \boldsymbol{\theta}^n).$$

$$\begin{aligned}
\boldsymbol{\theta}^1 &\leftarrow \boldsymbol{\theta}^1 + \alpha^1 \cdot \nabla_{\boldsymbol{\theta}^1} J(\boldsymbol{\theta}^1, \cdots, \boldsymbol{\theta}^m), \\
\boldsymbol{\theta}^2 &\leftarrow \boldsymbol{\theta}^2 + \alpha^2 \cdot \nabla_{\boldsymbol{\theta}^2} J(\boldsymbol{\theta}^1, \cdots, \boldsymbol{\theta}^m), \\
&\vdots \\
\boldsymbol{\theta}^m &\leftarrow \boldsymbol{\theta}^m + \alpha^m \cdot \nabla_{\boldsymbol{\theta}^m} J(\boldsymbol{\theta}^1, \cdots, \boldsymbol{\theta}^m).
\end{aligned}$$

» One agent's parameter changes will lead to variation of objective function of all agents

The i-th agent found $\boldsymbol{\theta}^i_\star = \underset{\boldsymbol{\theta}^i}{\text{argmax}}\, J^i(\boldsymbol{\theta}^1, \cdots, \boldsymbol{\theta}^n)$

» Meaning, if the agent finds the optimal parameter, once other agents change its policy, the agent has to find a new optimal parameter. This process will continue forever and can not converge

» Single agent: open AI gym, Stable Baseline v3

» Multi agent(no established lib): Ray Rllib, MARLlib. (distributed computing for centralized training and decentralized excution)

SMU

MARL: Convergence

Single-Agent Policy Learning

- Policy network: $\pi(a \mid s; \boldsymbol{\theta})$.
- State-value function: $V(s; \boldsymbol{\theta})$.
- $J(\boldsymbol{\theta}) = \mathbb{E}_S[V(S; \boldsymbol{\theta})]$ evaluates how good the policy is.
- Learn the policy network's parameter, $\boldsymbol{\theta}$, by

$$\max_{\boldsymbol{\theta}} J(\boldsymbol{\theta}).$$

- **Convergence:** $J(\boldsymbol{\theta})$ stops increasing.

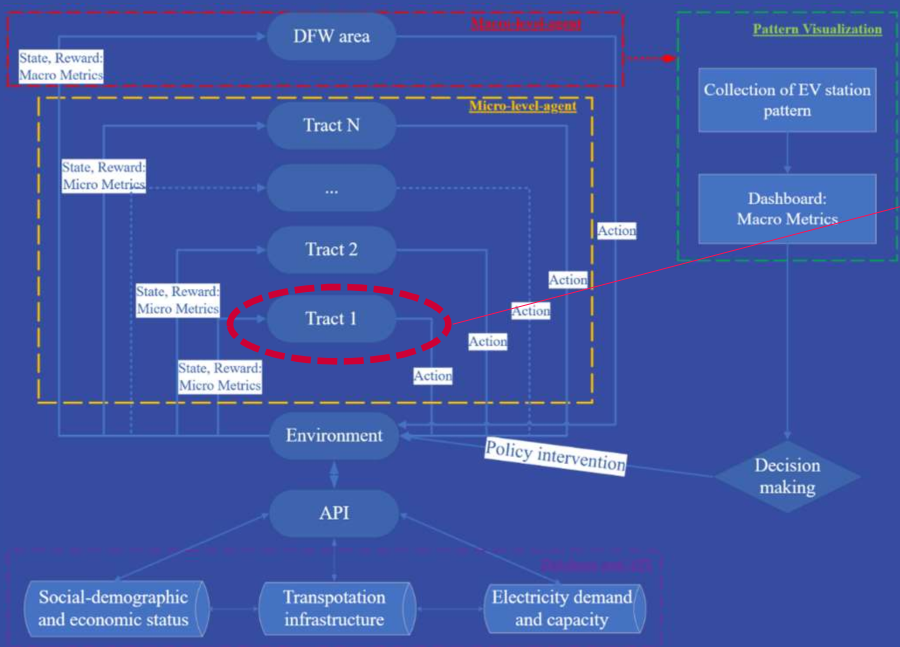
Multi-Agent Policy Learning

Nash Equilibrium

- While all the other agents' policy remain the same, the i-th agent cannot get better expected return by changing its own policy.
- Every agent is playing a best-response to the other agents' policies.
- Nash equilibrium indicates convergence because no one has any incentive to deviate.

- Convergence: No agent can get better expected return by improving its own policy.
- If there is only one agent, convergence means the objective function does not increase any more.
- If there are multiple agents, **Nash equilibrium** means convergence.

SMU



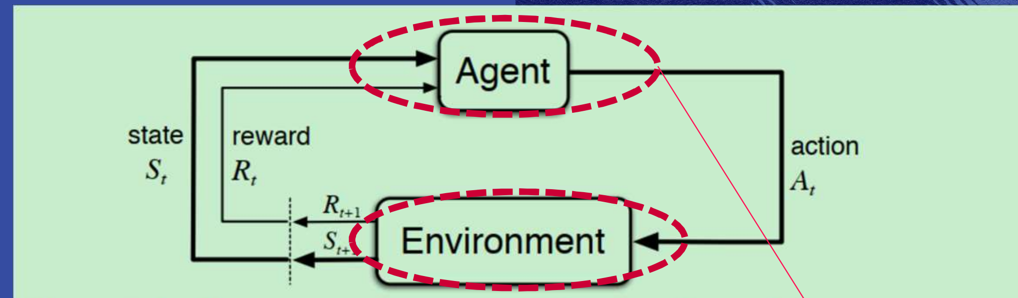


Figure 3.1: The agent–environment interaction in a Markov decision process.

Action Value Function:
- Q-table
- DQN

Orange frame: Single agent RL (common)
Orange + Green frame: Agent-based modeling architecture (a few)
Orange + Red frame: Multi agent RL architecture (some)
Orange + Red + Green frame: MARL-ABM with macro level controller (None & innovative)
Purple frame: database + data preprocess (common)
Entire framework is a decision-making platform driven by ABM integrated with MARL

SMU

Agent + Env: Tract

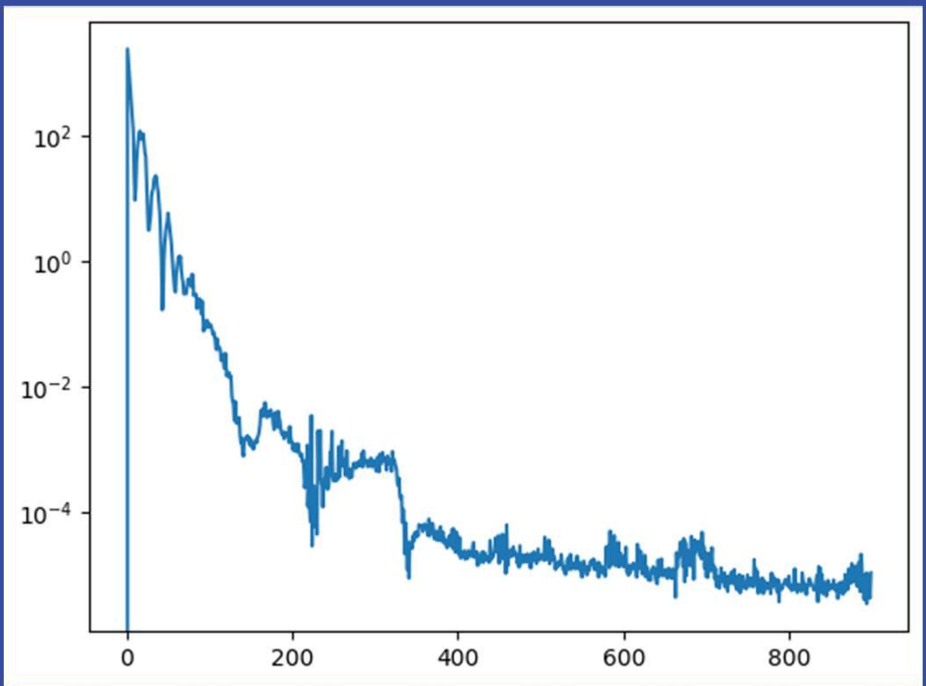
- Goal:
    - 1). Tract Equity: EVCSEI: 0 is the goal, negative: need more EVCS,
    - 2). Increase EVCS quantity
- TRACT: (Equity within a single tract)
    - Action: a ={EVCS cnt:[-1, 0 ,+1] }, Discrete(3, start=-1)
    - State: (Equity within a single tract)
        - S = [EVCS counts, s1,…,s24] = [EVCS count, var1,var2,…,var24]
        - observation_space = Box(low= 0, high=1, shape=(25,), dtype=int)
    - Reward: R(state, action, next_state)
        - EVCS count increase: +1; Average Monthly Electricity/Gas cost changes;
        - EVCSEI should be close to 0, if 0, high reward, otherwise low reward
    - Terminated state:
        - when B25133_002E (gas cost) – 50*S <0 (assuming gas cost reduce by 50 with one EVCS installed)
        - when B25132_009E(electricity cost) + 20*S > sum(gas, electricity cost)

```python
# Apply action and move to next state
self.state[0] += self.action_dict[action]
self.state[22] -= self.action_dict[action]*50 #gas cost reduced by 50 with one EVCS installed

# Check if it is done
self.maxlen -=1
if self.state[0] <0 or self.state[0] >200:
    isTerminated =True
# Terminated state1: when S - monthly gas cost/50 <0
elif self.state[22] - 50*self.state[0] <=0:
    isTerminated =True
# Terminated state2: when S - monthly electricity cost/20 <0
elif self.state[21] + 20*self.state[0] > ( self.state[22] + self.state[21]) :
    isTerminated =True
```

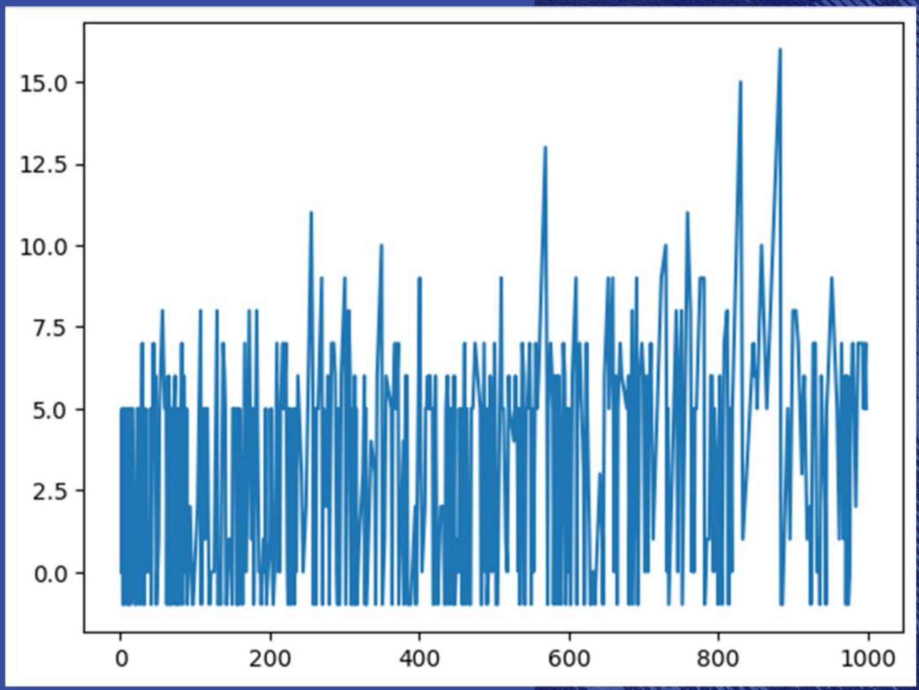
Terminal state:
Limit average monthly gas and electricity cost

```python
# assume increasing EVCS_cnt will decrease monthly gas cost "B25133_002E", index 21
s_next = s + a
# increasing 1 EVCS will decrease average monthly gas cost by 50
# increasing 1 EVCS will increase average monthly electricity cost by 50
X_next = X_vars_tract
X_next[21] -= a*50
X_next[20] += a*40

d_EVCSEI = EVCSEI(s_next, X_next) - EVCSEI(s, X_vars_tract)

if abs( EVCSEI(s_next, X_next) ) < abs( EVCSEI(s, X_vars_tract) ): # if EVCSEI_next is becomeing closer to 0
    reward = 5
elif s_next>s: # we encourage to increase EVCS count rather than change other vars0-vars24.
    reward = 2
elif s_next==s:
    reward  = 1
elif s_next<s:
    reward  = -1
elif s_next ==0:
    reward = -10
else:
    reward = -1
```

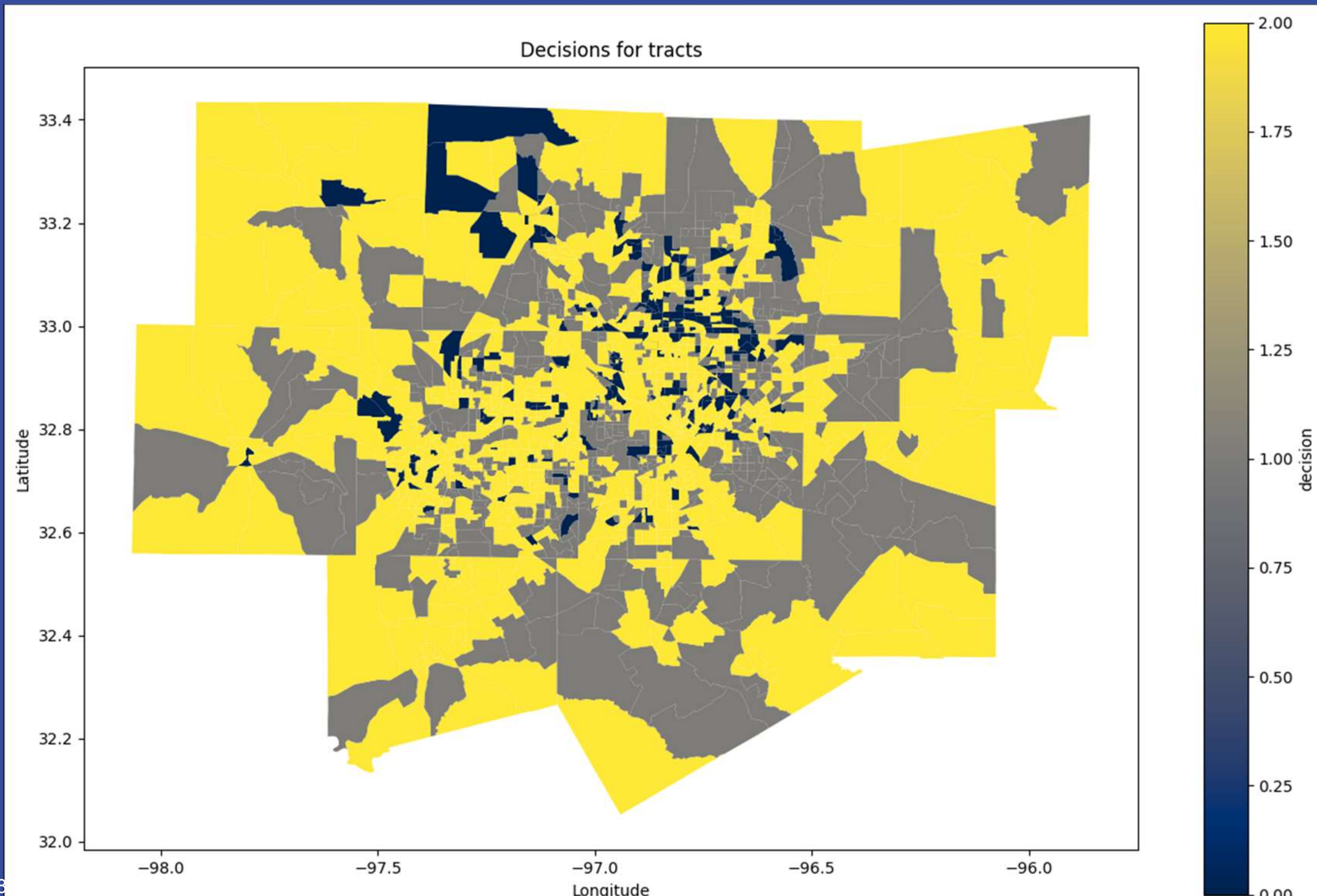
Reward design
EVCSEI close to 0 => higher reward (+5)
EVCS cnt increased => positive reward (+1)
EVCS cnt =0 => heavy penalty (-10)



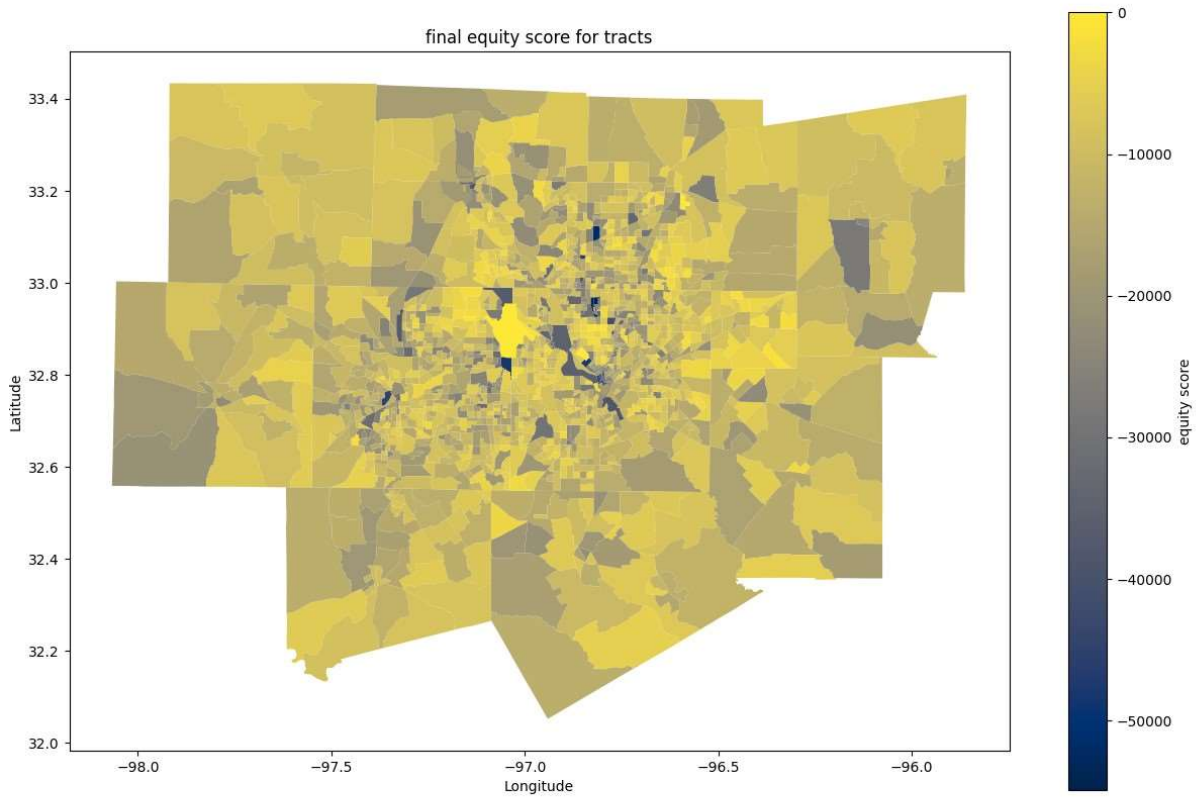
10^2
10^0
10^{-2}
10^{-4}
0
200
400
600
800



15.0
12.5
10.0
7.5
5.0
2.5
0.0
0
200
400
600
800
1000



Decisions for tracts
33.4
33.2
33.0
32.8
32.6
32.4
32.2
32.0
Latitude
−98.0
−97.5
−97.0
−96.5
−96.0
Longitude
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
decision


final equity score for tracts
Latitude
Longitude
33.4
33.2
33.0
32.8
32.6
32.4
32.2
32.0
−98.0
−97.5
−97.0
−96.5
−96.0
equity score
0
−10000
−20000
−30000
−40000
−50000

Agent + Env: Macro controller

- Goal:
  - 1). Equity: DFW EVCSEI: 0 is the goal, negative: need more EVCS,
  - 2). To increase or limit total quantity of EVCS | Understand effect of electricity price changes on EVCS quantity
- DFW: (Equity across the tracts)
  - Action: a =[a0…..a24] or {Electricity price:[-10%, 0 ,+10%] }, Discrete(3, start=-1)
  - Reward: EVCSEI should be close to 0, if 0, high reward, otherwise low reward
  - State: S =[s0,…,s24]

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Sustainable Cities and Society 83 (2022) 103978

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

Examining spatial disparities in electric vehicle charging station placements using machine learning

Avipsa Roy[a,b,*], Mankin Law[a]

[a] Department of Urban Planning and Public Policy, University of California, 300 Social Ecology I, Irvine, CA 92697, USA
[b] Institute of Transportation Studies, University of California, Irvine, USA

ous work (Law & Roy, 2021; Shahriar et al., 2021), and preprocessed i

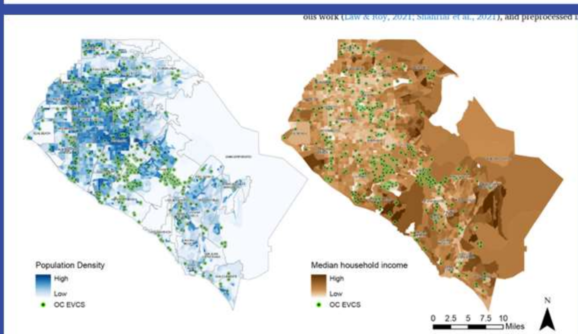
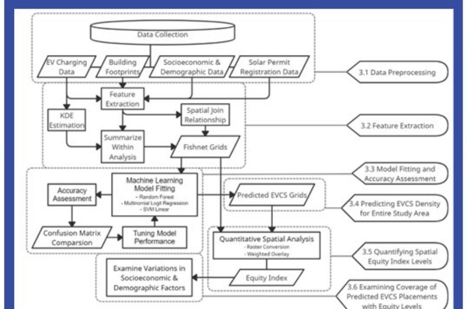


Fig. 1. Spatial distribution of existing EV charging stations across Orange County w.r.t to (a) population density and (b) median household income distribution.



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Sustainable Cities and Society, 24 January 2023
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Research article
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Sustainable Cities and Society, May 2018
Soukaina Boudoudouh, Mohamed Maâroufi

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Energy Research & Social Science 91 (2022) 102760

Contents lists available at ScienceDirect

Energy Research & Social Science

journal homepage: www.elsevier.com/locate/erss

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Original research article

No electricity considered

Inequality and the future of electric mobility in 36 U.S. Cities: An innovative methodology and comparative assessment

Patricia Romero-Lankao *, Alana Wilson, Daniel Zinny-Schmitt

National Renewable Energy Laboratory, Golden, CO 80401, United States of America

Typology

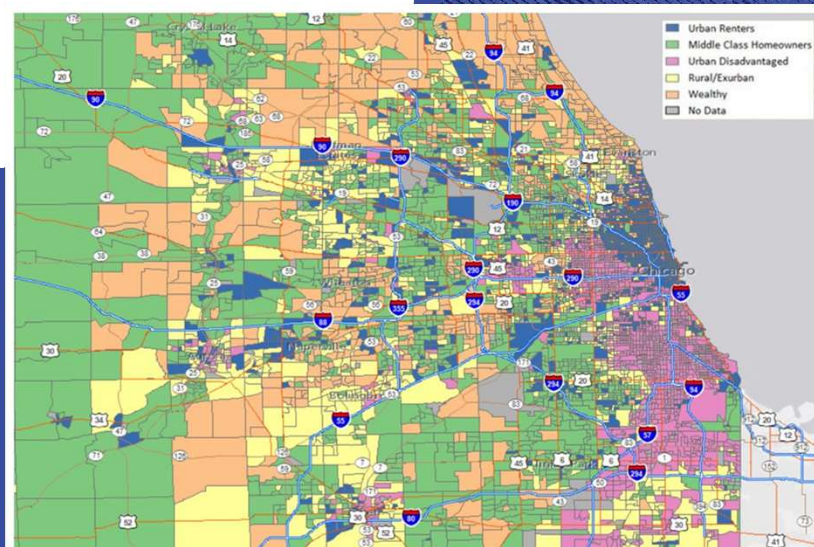

Fig. 5. Socio-spatial distribution of MUSTs in Chicago.

IF=6.8

Computers, Environment and Urban Systems 101 (2023) 101949

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Computers, Environment and Urban Systems

journal homepage: www.elsevier.com/locate/ceus

No electricity considered

An agent-based modeling approach for public charging demand estimation and charging station location optimization at urban scale

Zhiyan Yi [a], Bingkun Chen [b], Xiaoyue Cathy Liu [c,*], Ran Wei [d], Jianli Chen [e], Zhuo Chen [b]

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[b] Department of Civil Engineering, Monash University, Australia
[c] Department of Civil & Environmental Engineering, University of Utah, 110 Central Campus Dr. RM 2137, Salt Lake City, UT 84112, United States of America
[d] School of Public Policy, University of California, Riverside, United States of America
[e] Department of Civil & Environmental Engineering, University of Utah, 110 Central Campus Dr. RM 2032, Salt Lake City, UT 84112, United States of America

ARTICLE INFO

Keywords:
Electric vehicles
Agent-based simulation
Charging demand modeling
Charging infrastructure
Maximal coverage location problem

ABSTRACT

As the market penetration of electric vehicles (EVs) increases, the surge of charging demand could potentially overload the power grid and disrupt infrastructure planning. Hence, an efficient deployment strategy of electrical vehicle supply equipment (EVSE) is much needed. This study attempts to address the EVSE problem from a microscopic perspective by formulating the problem in two steps: public charging demand simulation and charging station location optimization. Specifically, we apply agent-based modeling approach to produce high-resolution daily driving profiles within an urban-scale context using MATSim. Subsequently, we perform EV assignment based on socioeconomic attributes to determine EV adopters. Energy consumption model and public charging rule are specified for generating synthetic public charging demand and such demand is validated against real-world public charging records to guarantee the robustness of simulation results. In the second step, we apply a location approach – capacitated maximal coverage location problem (CMCLP) model – to reallocate existing charging stations with the objective of maximizing the coverage of total charging demands generated from the previous step under the budget and load capacity constraints. The entire framework is capable of modeling the spatiotemporal distribution of public charging demand in a bottom-up fashion, and provide practical support for future public EVSE installation.

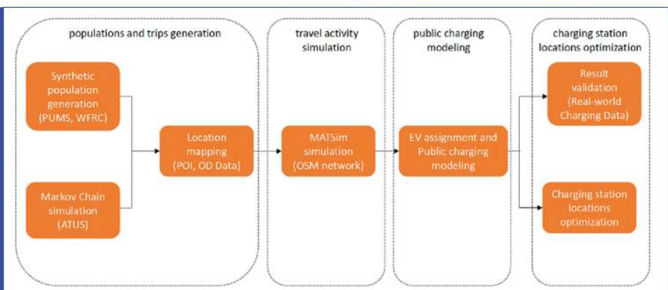
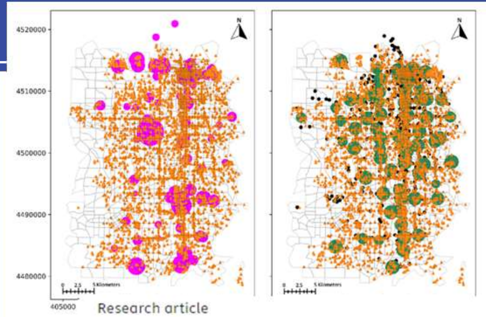


Fig. 1. Model development framework.



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Energy

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They use network science

From different perspective, We Intergrate RL to ABM

EV charging station deployment on coupled transportation and power distribution networks via reinforcement learning

Zhonghao Zhao, Carman K.M. Lee [*], Jiage Huo

Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hong Kong, 999077, China

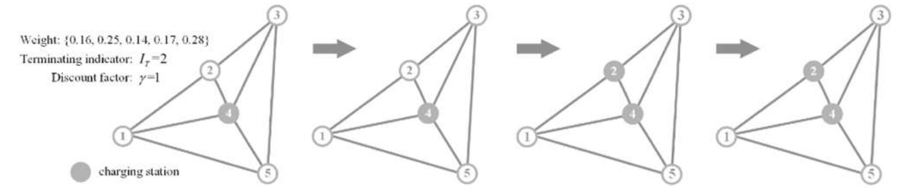
ARTICLE INFO

Handling Editor: X Ou

Keywords:
Electric vehicle
Charging station deployment
Coupled network
Reinforcement learning

ABSTRACT

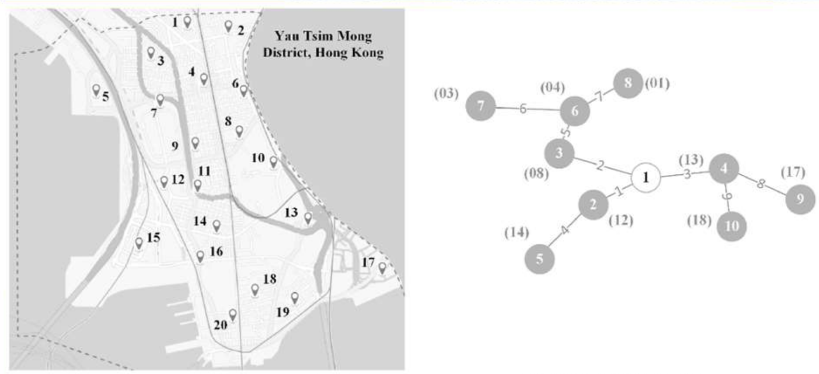
This study addresses the optimal electric vehicle (EV) charging station deployment problem (CSDP) on coupled transportation and power distribution networks, which is one of the critical issues with the mass adoption of EVs in the recent years. In contrast to existing works that mainly employ heuristics and exact algorithms, we propose a finite-discrete Markov decision process (MDP) formulation defined in a reinforcement learning (RL) framework to mitigate the curse of dimensionality problem. The RL-based approach aims to determine the location of a set of EV charging stations with limited capacity by minimizing the total investment cost while satisfying the coupled network constraints. Specifically, a long short-term memory (LSTM)-based recurrent neural network (RNN) with an attention mechanism is used to train the model based on an offline strategy. The model parameters are learned by the policy gradient algorithm with a learned baseline function. Numerical experiments on multiple problem sizes are conducted to assess the efficiency and feasibility of the proposed solution method. We experimentally show that our approach is efficient to solve the CSDP and outperforms other baseline approaches in solution quality with competitive computational time.



Decoding/Time Step:	Initialization	$t=1$	$t=2$	$t=3$
State:	(0,0,0,0,0)	(0,0,0,0,0)	(0,0,0,1,0)	(0,1,0,1,0)
Softmax Distribution:	(0,0,0,0,0)	(0.000, 0.288, 0.006, **0.624**, 0.082)	(0.033, **0.947**, 0.011, 0.007, 0.002)	(0.001, **0.586**, 0.018, 0.324, 0.071)
Action:	—	4	2	2
Total Cost:	0	10^7	1.77×10^6	1.77×10^6
Reward	0	-10^7	8.23×10^6	0
Capacity	—	—	(0,22,0,15,0)	(0,22,0,15,0)

Optimal Results (obtained by CPLEX): (0,22,0,15,0) Final Reward: $\mathcal{R}=-1.77\times10^6$

Fig. 3. Planning results of the illustrative example.



(a) The urban transportation network of Yau Tsim Mong District

(b) Power distribution network

Fig. 4. The diagram of the coupled network.

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Simulation Modelling Practice and Theory

journal homepage: www.elsevier.com/locate/simpat

We focus on RL driven agent based modeling, and use EV station placement as case study

Dynamic-data-driven agent-based modeling for the prediction of evacuation behavior during hurricanes

Seunghan Lee[a], Saurabh Jain[b], Keeli Ginsbach[b], Young-Jun Son[b,*]

[a] Department of Industrial and Systems Engineering, University at Buffalo, SUNY 211 Putnam Way, Buffalo, NY 14260, United States
[b] Department of Systems and Industrial Engineering, The University of Arizona, 1127 James E. Rogers Way, Tucson, AZ 85721, United States

ARTICLE INFO

Keywords:
Dynamic-data-driven modeling
Evacuation behaviors
Hurricanes
Disaster management
Agent-based simulation

ABSTRACT

Establishing an efficient disaster management strategy against severe natural disasters is essential to mitigate and relieve their catastrophic consequences. In order to understand the situation during such devastating events, it is crucial to incorporate individuals' behaviors and their decision-making processes, which requires an amalgamation of information from various sources such as survey data, information regarding location and intensity of disasters, government's policies, and supplies in the affected region. This work proposes a dynamic-data-driven model for individual decision-making processes capable of tracking people's preference value over time, incorporating dynamic environmental changes using Bayesian updates. An agent-based simulation was used to model each of the components vital to devise an effective disaster management strategy. Moreover, the proposed model allows deriving quantitative relationships among people's evacuations, their demographic information, and risk perception based on environmental changes, including traffic status, gas outage, and government notice. For this study, the authors considered Florida's situations during hurricanes Irma, Michael, and Dorian in 2017, 2018, and 2019. What-if analyses were also conducted to find the best disaster management policy for government agencies to minimize the hurricane's effect, which will help prepare for future disaster situations.

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Applied Energy 325 (2022) 119771

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Optimizing equity in energy policy interventions: A quantitative decision-support framework for energy justice

Miguel Heleno [a,*], Benjamin Sigrin [b], Natalie Popovich [a], Jenny Heeter [b], Anjuli Jain Figueroa [c], Michael Reiner [c], Tony Reames [c]

[a] Lawrence Berkeley National Laboratory, Berkeley, CA, USA
[b] National Renewable Energy Laboratory, Golden, CO, USA
[c] US Department of Energy, Washington DC, USA

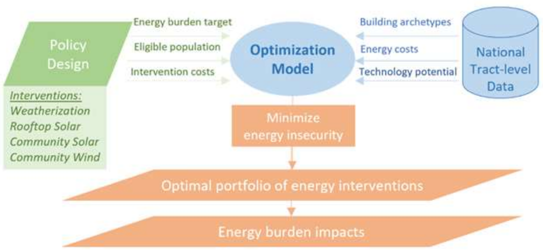

Fig. 1. Methodology overview.

Research article

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Engineering Applications of Artificial Intelligence 115 (2022) 105299

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Engineering Applications of Artificial Intelligence

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Multiple attribute group decision making based on quasirung orthopair fuzzy sets: Application to electric vehicle charging station site selection problem

Mijanur Rahaman Seikh*, Utpal Mandal

Department of Mathematics, Kazi Nazrul University, Asansol 713 340, India

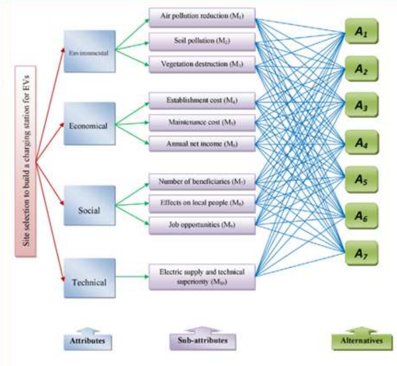

Fig. 3. Hierarchical framework of EVCS site selection.

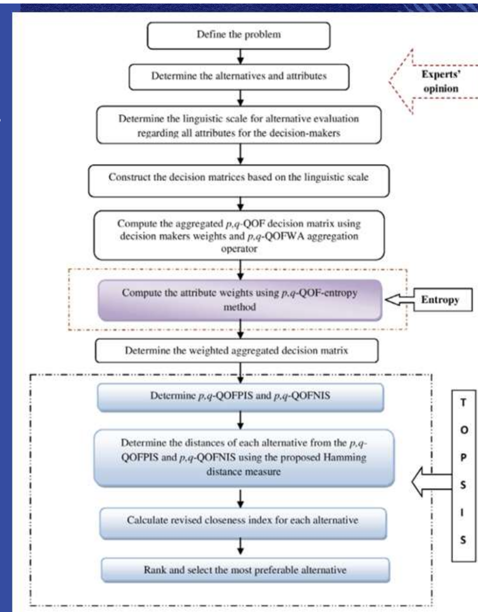

Fig. 2. Framework of the proposed method.

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Engineering Applications of Artificial Intelligence

Volume 125, October 2023, 106701

Multi-agent model based proactive risk management for equity investment

Daiya Mita[a b], Akihiko Takahashi[b]

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Engineering Applications of Artificial Intelligence

Volume 33, August 2014, Pages 91-98

Agent-based modeling and simulation of a smart grid: A case study of communication effects on frequency control

O. Kilkki, A. Kangasrääsiö, R. Nikkilä, A. Alahäivälä, I. Seilonen

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Abstract

A smart grid is the next generation power grid focused on providing increased reliability and efficiency in the wake of integration of volatile distributed energy resources. For the development of the smart grid, the modeling and simulation infrastructure is an important concern. This study presents an agent-based model for simulating different

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Plan

» Work on the 2 papers at the same time

» By the year end, should be submitted.