CARTO

Unlocking Smarter Property Risk Assessments with Spatio-Temporal Crime Insights and CARTO

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GeoPython 2025

Basel Switzerland February 24-26

https://2025.geopython.net

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Data Scientist @CARTO

CARTO

Agenda

- Intro to cloud native CARTO
- Intro to the Analytics Toolbox and Workflows
- Use case: Unlocking Smarter Property Risk Assessments with Spatio-Temporal Crime Insights and CARTO
- Questions and Answers

CARTO

Before we begin

All the content for this workshop including a transcript, links to all maps and code can be found in:

https://rb.gy/geesg9

SCAN ME

CARTO

If you haven’t already...

📄 For this session, you’ll need a CARTO account! If you don’t have one, you can set up a free 14-day trial at **app.carto.com**

❗ There is a maximum of one CARTO account per email address. If you have previously set up a free trial with your email, we recommend using an alternative email address for this session. If you run into any issues setting up an account, please contact support@carto.com.

SCAN ME

https://rb.gy/geesg9

The leading platform for Location Intelligence and Spatial Data Science

/CartoDB

With an end to end platform:

Technology

Managed cloud or on-premises platform

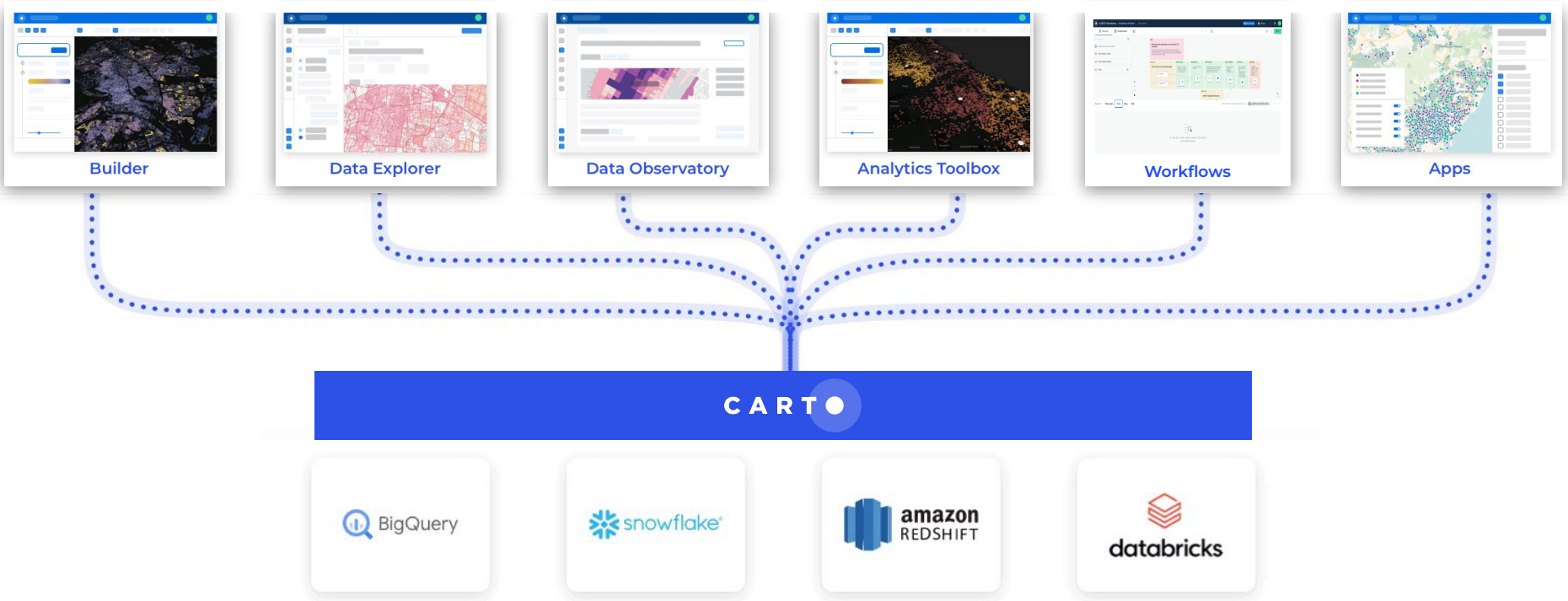
Data

Open and premium location data streams

Services

Ongoing enablement programs and custom engagements

CARTO brings together cloud connectivity, visualization, spatial analysis and development capabilities in a unified workspace.

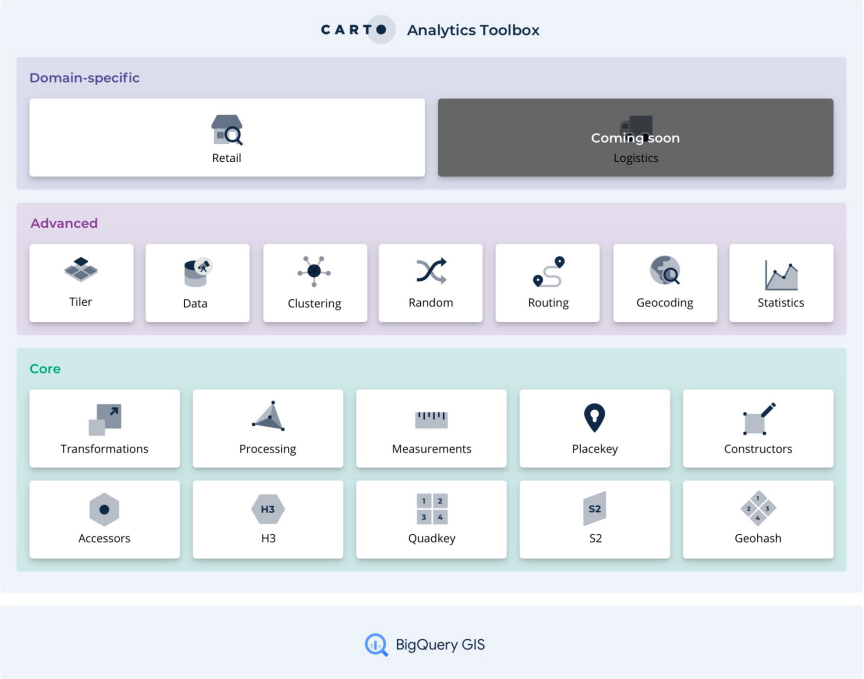


Analytics Toolbox

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 960401.

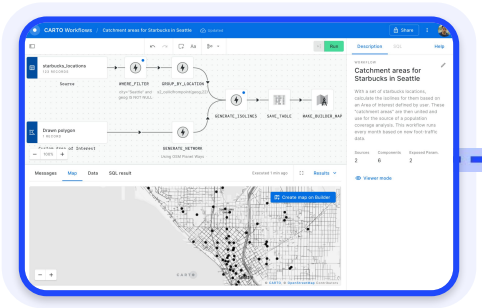
Overview

- Set of UDFs and Stored Procedures that unlock advanced Spatial Analytics **natively** within the data warehouses.
- Executed directly from your client, using **simple SQL** commands.
- Separated in **different levels** of abstraction, with core, advanced and domain specific functions (e.g. telco).



Workflows

A new UI to design Spatial SQL workflows



User designs workflows in CARTO

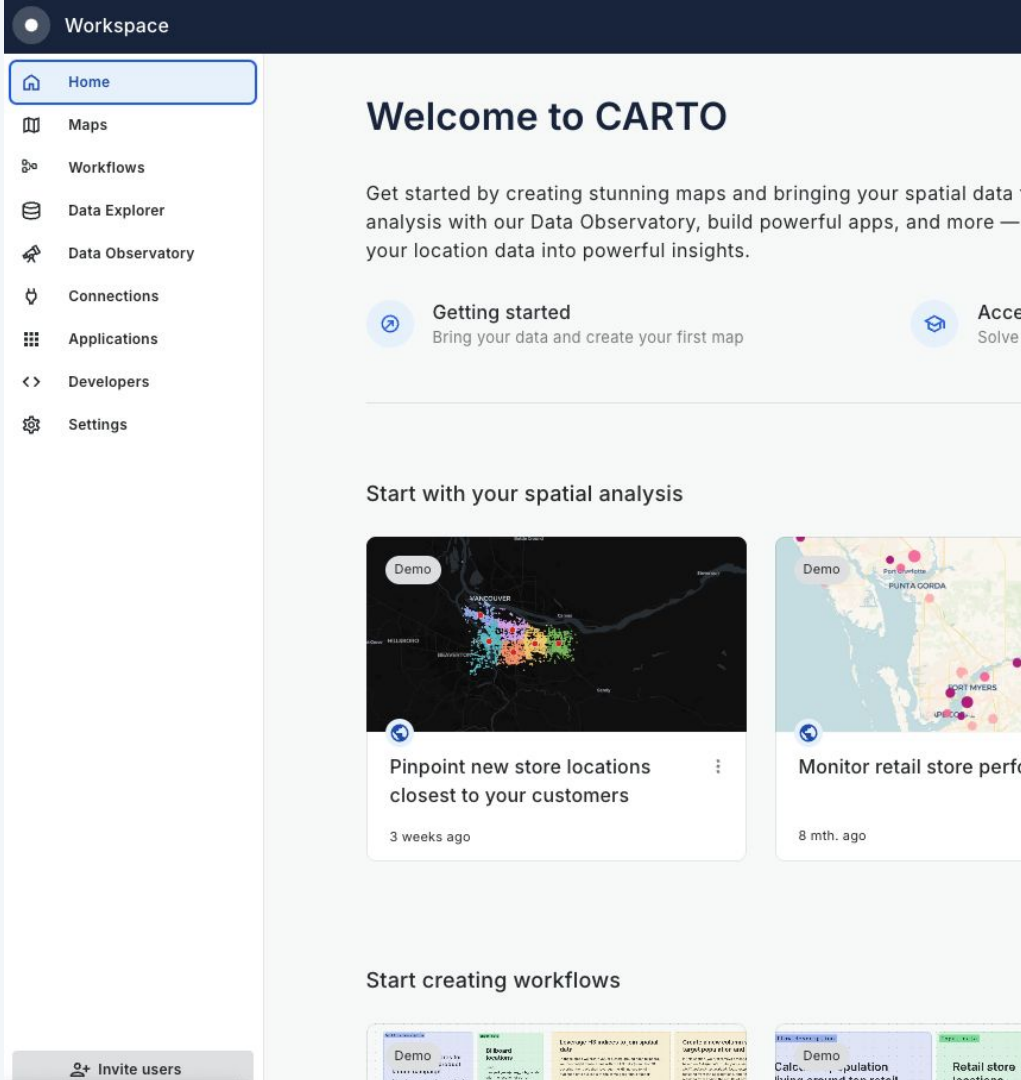
Workflows are compiled into SQL

Workflows are executed on your data warehouse

CARTO Platform

A Guided Tour

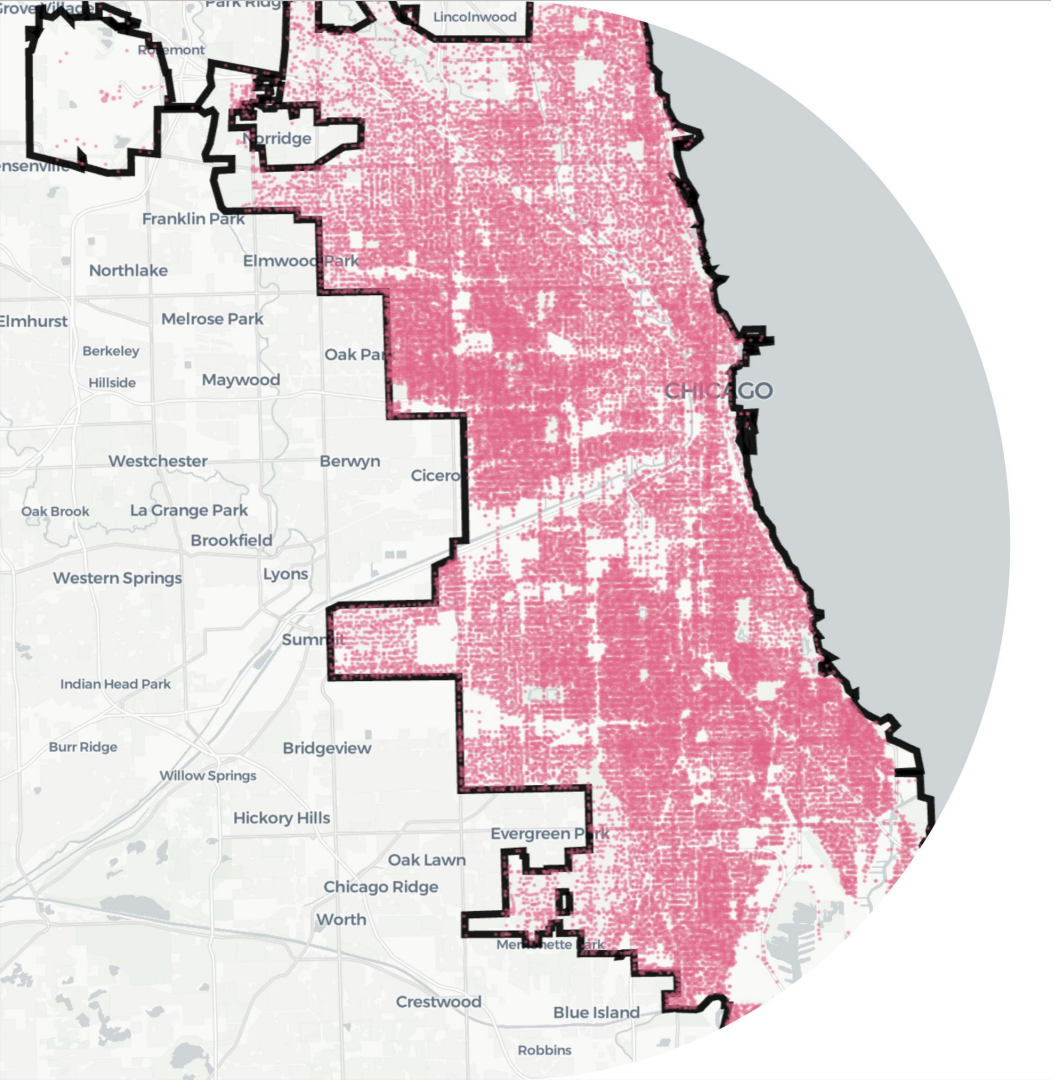
https://app.carto.com/



It’s time for a real world example!

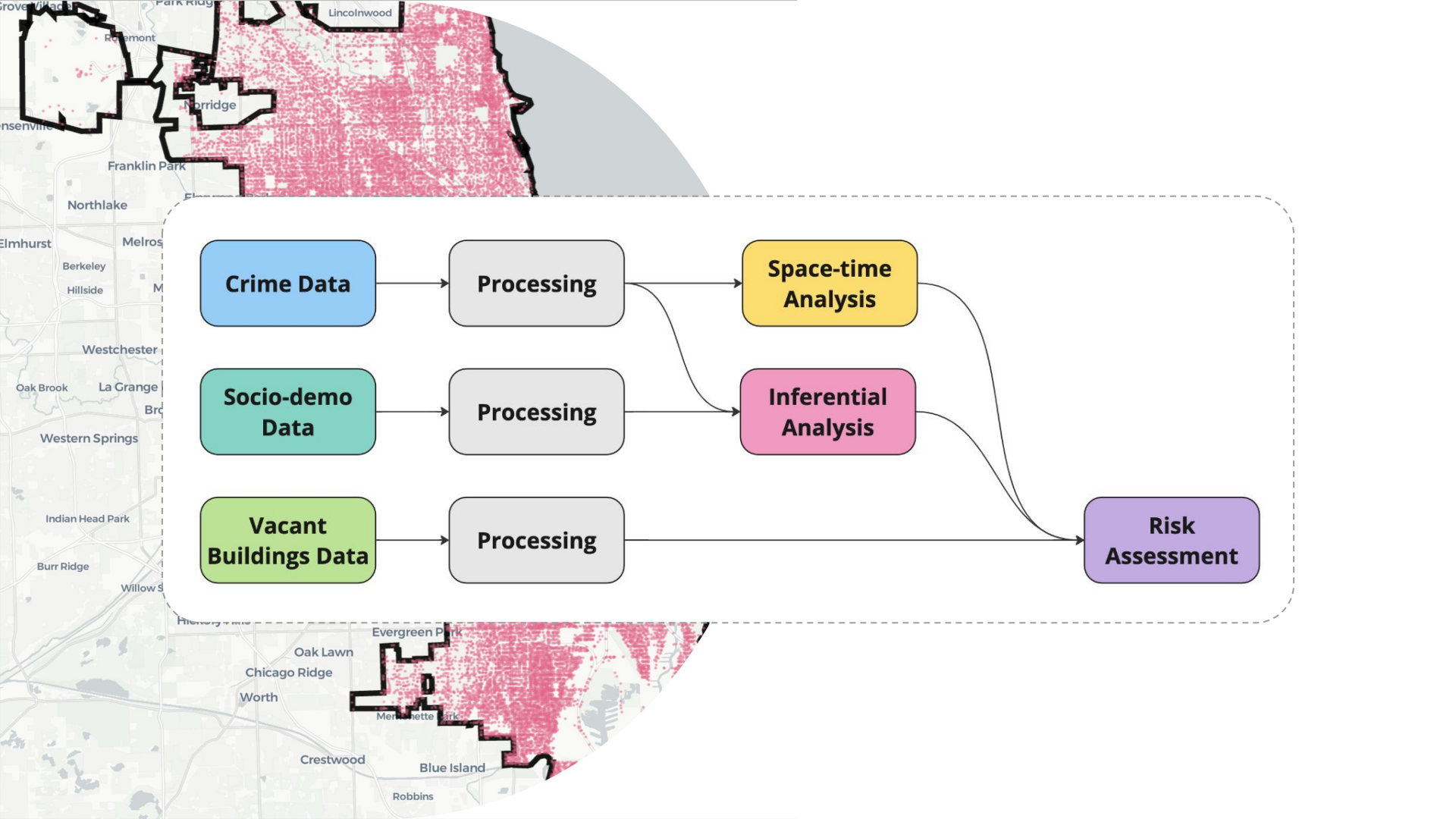
- How to take advantage of cloud native data warehouses to process, visualize, and analyze spatio-temporal big data
- How to use CARTO to analyse and model the spatial distribution and temporal evolution of real-world datasets
- How to use CARTO to create workflows and visualizations that provide decision-makers with easy access to critical insights

Unlocking Smarter Property Risk Assessments with Spatio-Temporal Crime Insights



We'll get hands-on with CARTO, showing you how to **analyze** the **patterns and changes** in violent crimes **over time and space**.

We'll learn how insurers can use the results from this analysis to **improve portfolio management** by better assessing non-financial, location-based risks related to not just crime, but also to other perils, like floods, hurricanes, hail.


Crime Data
Processing
Space-time Analysis
Socio-demo Data
Processing
Inferential Analysis
Vacant Buildings Data
Processing
Risk Assessment
Lincolnwood
Franklin Park
Northlake
Elmhurst
Melros
Berkeley
Hillside
Westchester
Oak Brook
La Grange
Western Springs
Indian Head Park
Burr Ridge
Evergreen Park
Oak Lawn
Chicago Ridge
Worth
Crestwood
Blue Island
Robbins

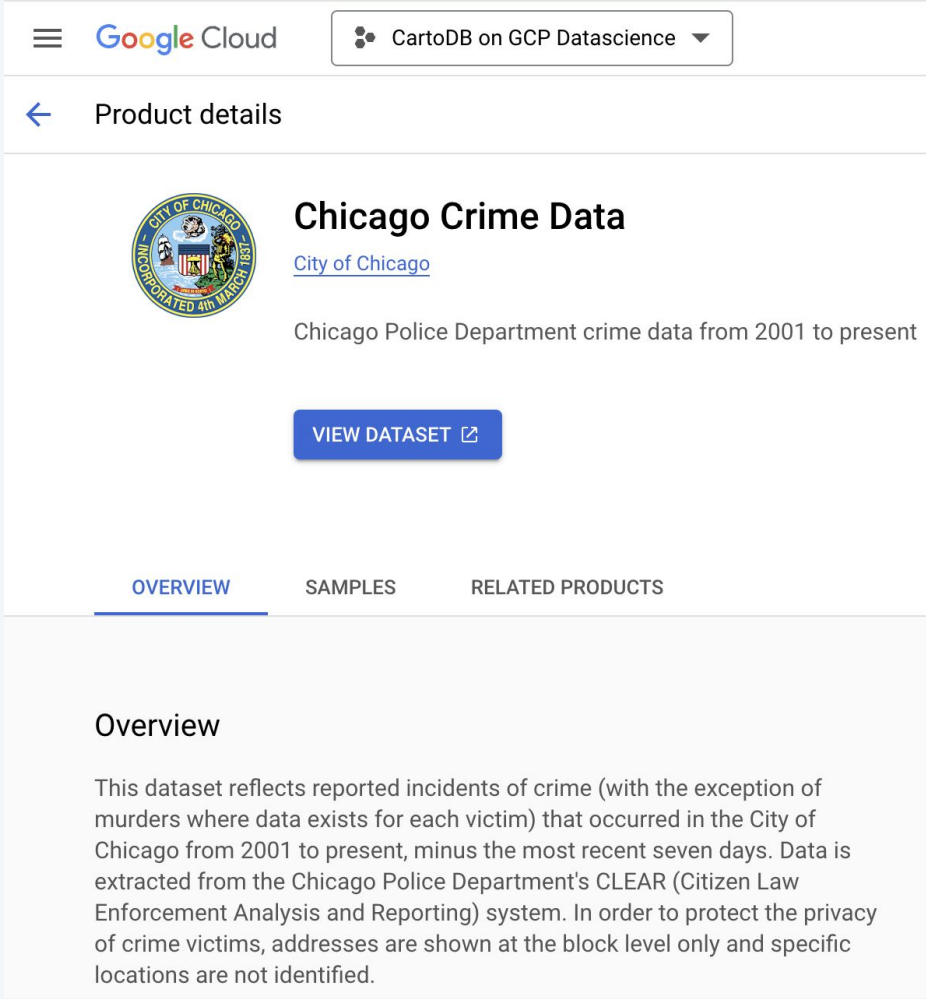
Presenting the data

Violent Crime Data

- **Crime incidents** in Chicago from 2001-present
- It features **one row per report**
- The geo support is **the Census block's lon/lat coordinates**

Can be found in:

Google BigQuery public marketplace
@bigquery-public-data.chicago_crime.crime

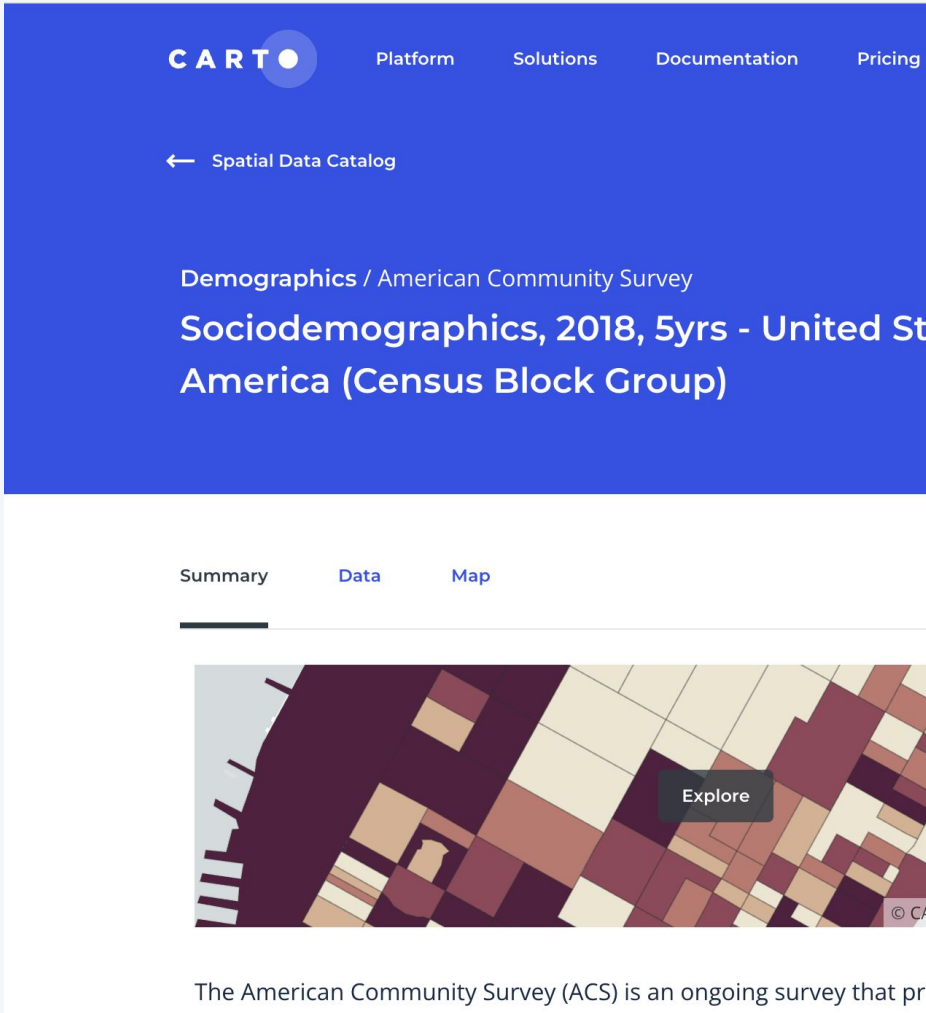


US Census

- **American Community Survey** 5-years and 1-year estimates
- It features:
  - The **geometry** of each Census block group
  - Population, median rent, etc.

Can be found in:

Subscribing to the ACS data in CARTO spatial catalog

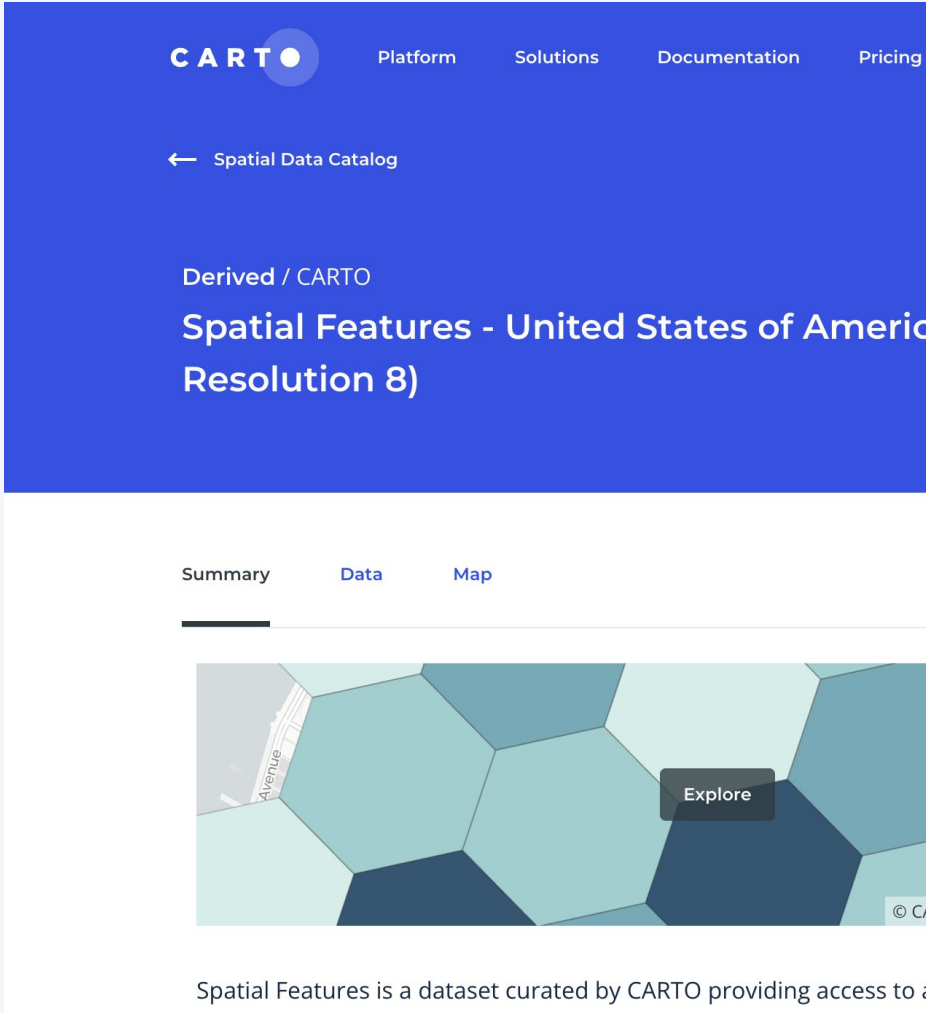


CARTO Spatial Features

- **Derived** variables including demographics, points of interest, and climatology, with **global** coverage
- It features:
  - The **H3** cell
  - The urbanity level

Can be found in:

Subscribing to CARTO Spatial Features data in CARTO spatial catalog

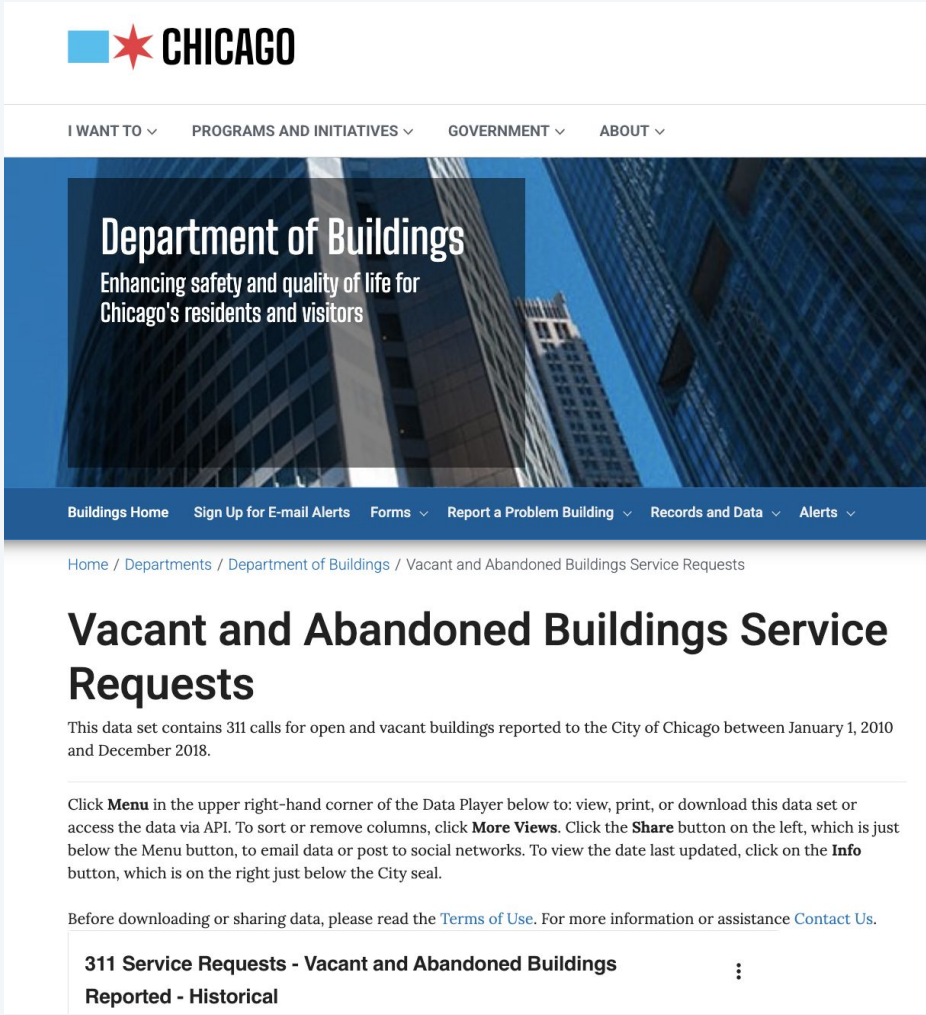


Vacant Buildings

- 311 calls for open and vacant buildings [reported to the City of Chicago]
- Address location, vacant or occupied status; if the building appears dangerous or hazardous...

Can be found in:

`cartobq.sdsc24_ny_workshops.CHI_boundary_311_vacant_buildings`



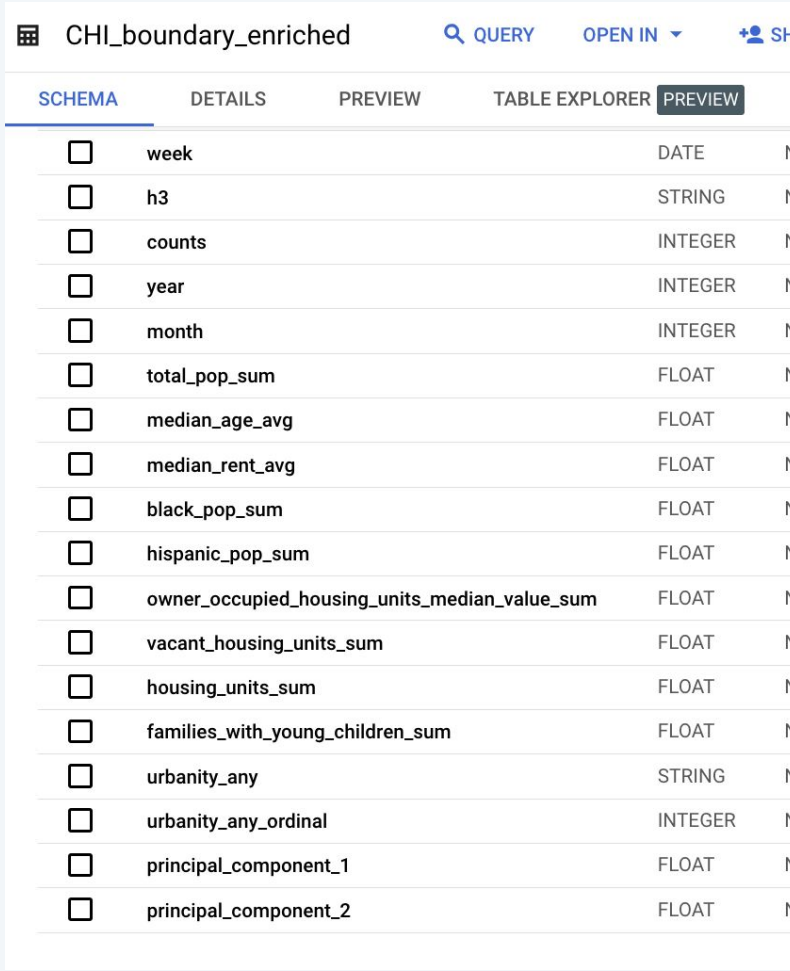
Pre-processing the data

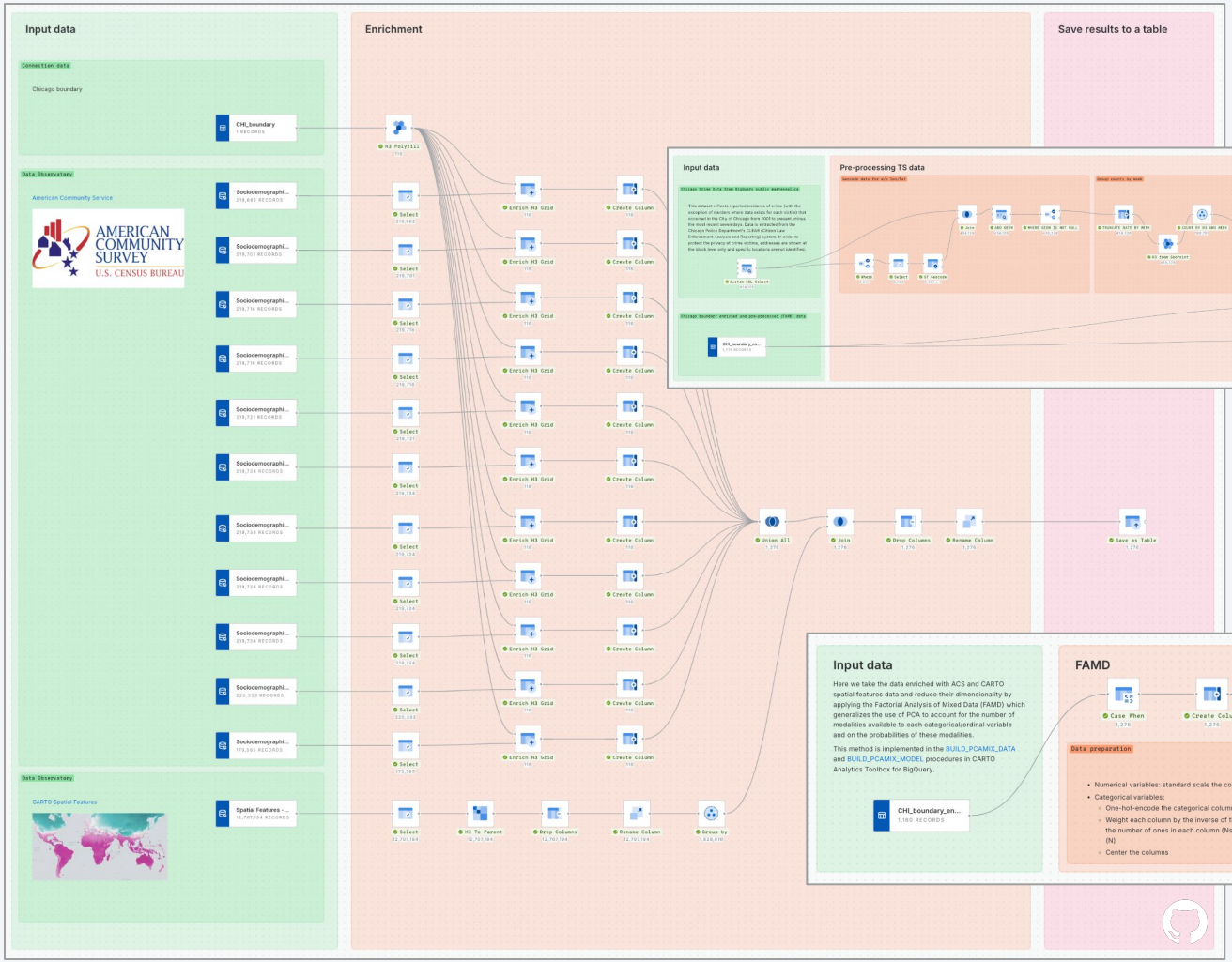
We've already...

1. Transformed all input sources into a regular grid of **Spatial Indexes** through **Enrichments**
2. Reduced the dimensionality of the enriched data to reduce model complexity (we will use this data to model crime counts) using the **Factorial Analysis of Mixed Data** algorithm

Processed data is available through BQ:

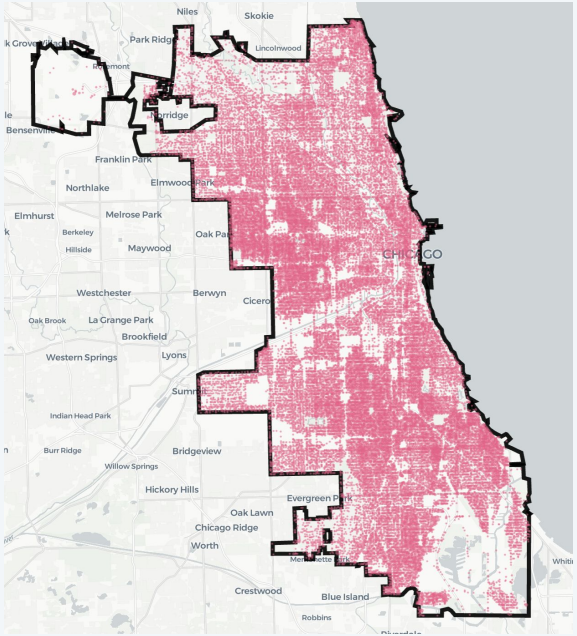
`cartobq.sdsc24_ny_workshops.CHI_boundary_enriched`

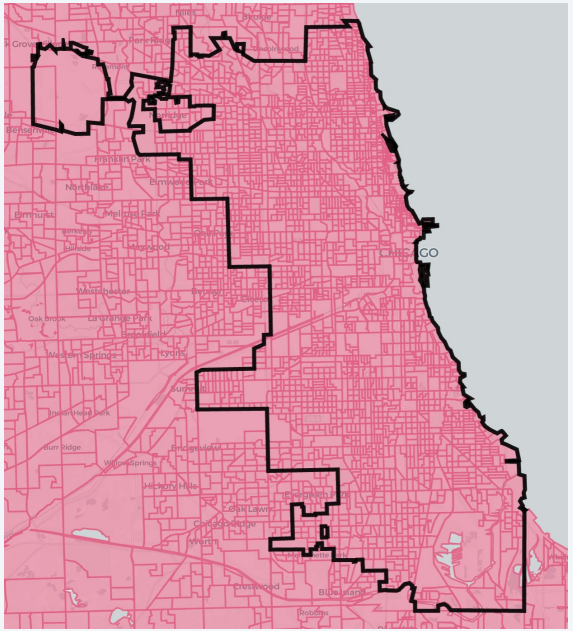


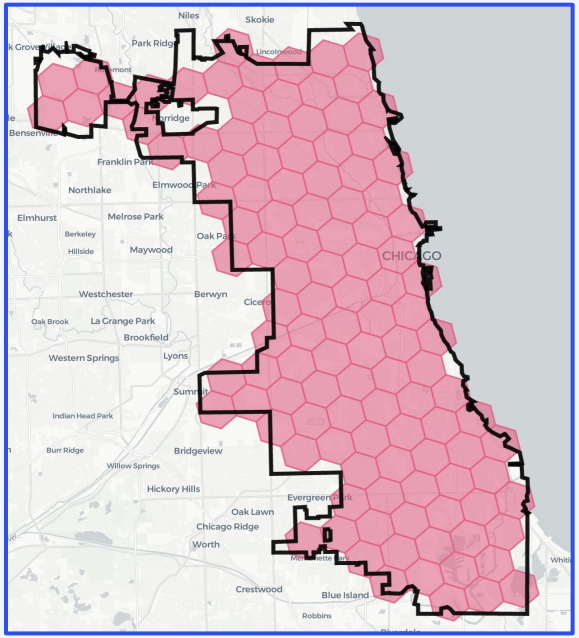

Input data
Connection data
Chicago boundary
CHI_boundary
1 RECORDS
Data Observatory
American Community Service
AMERICAN COMMUNITY SURVEY
U.S. CENSUS BUREAU
Sociodemographi...
219,662 RECORDS
218,701 RECORDS
219,716 RECORDS
219,776 RECORDS
219,721 RECORDS
219,734 RECORDS
219,734 RECORDS
219,734 RECORDS
219,726 RECORDS
220,333 RECORDS
179,865 RECORDS
Data Observatory
CARTO Spatial Features
Spatial Features -...
12,707,164 RECORDS
Enrichment
H3 Polyfill
Select
Enrich H3 Grid
Create Column
Union All
Join
Drop Columns
Rename Column
Group by
H3 To Parent
Save as Table
Save results to a table
Input data
Chicago Crime Data from Bigquery public marketplace
This dataset reflects reported incidents of crime (with the exception of murders where data exists for each victim) that occurred in the City of Chicago from 2001 to present, minus the most recent seven days. Data is extracted from the City of Chicago's Citizen Law Enforcement Analysis and Reporting system. In order to protect the privacy of crime victims, addresses are shown at the block level only and specific locations are not identified.
Custom SQL Select
Chicago boundary enriched and pre-processed (FAMD) data
CHI_boundary_en...
1,160 RECORDS
Pre-processing TS data
Seconds data for w/o Seattel
Group counts by week
Filling missing dates w/ zeros
Join with the enriched data
Where
Select
ST_Geogpoint
Join
ADD GEOM
MAKE GEOM IS NOT NULL
TRUNCATE DATE BY WEEK
COUNT BY H3 AND WEEK
H3 FROM GeoPoint
ADD MIN-MAX dates
GAP FILING
CREATE YEAR COLUMN
Select Distinct
Custom SQL Select
Drop Columns
ADD SEASON
CUSTOM JOIN
Save as Table
Save results to a table
Input data
Here we take the data enriched with ACS and CARTO spatial features data and reduce their dimensionality by applying the Factorial Analysis of Mixed Data (FAMD) which generalizes the use of PCA to account for the number of modalities available to each categorical/ordinal variable and on the probabilities of these modalities.
This method is implemented in the BUILD_PCAMIX_DATA and BUILD_PCAMIX_MODEL procedures in CARTO Analytics Toolbox for BigQuery.
CHI_boundary_en...
1,160 RECORDS
FAMD
Case When
Create Column
CUSTOM JOIN
Data preparation
Numerical variables: standard scale the columns to get their z-scores
Categorical variables:
One-hot-encode the categorical columns to get their indicator matrix
Weight each column by the inverse of the square root of its probability, given by the number of ones in each column (Ns) divided by the number of observations (N)
Center the columns
BUILD_PCAMIX_DATA
Run FAMD
BUILD_PCAMIX_MODEL
Save results to a table
Save as Table

We've already...

1. Transformed all input sources into a regular grid of **Spatial Indexes** through **Enrichments**

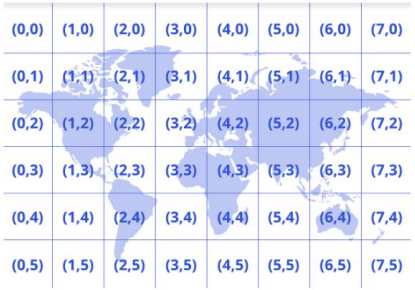




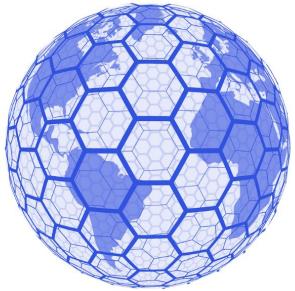


Spatial Indexes

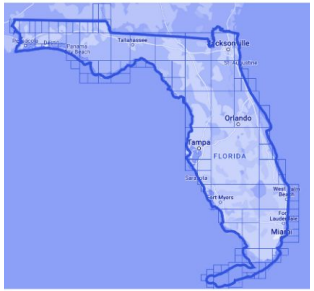
Multi-resolution, hierarchical grids that are “geolocated” by a short reference string, rather than a complex geometry:



Quadbin



H3



S2

Spatial Indexes

8a2aa84ec307fff

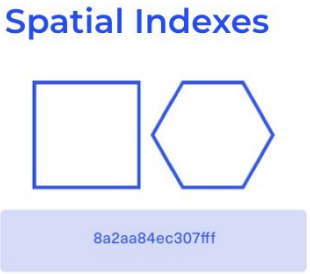
Geometries

POLYGON((-96.196141 41.125515, -96.195606 41.125514, -96.181864 41.125507, -96.177078 41.125474, -96.167733 41.125456, -96.160565 41.125456, -96.154682 41.125429, -96.151094 41.125414, -96.138848 41.125395, -96.138454 41.125394, -96.138381 41.125394, -96.137158 41.125391, -96.130043 41.125377, -96.1301...))*

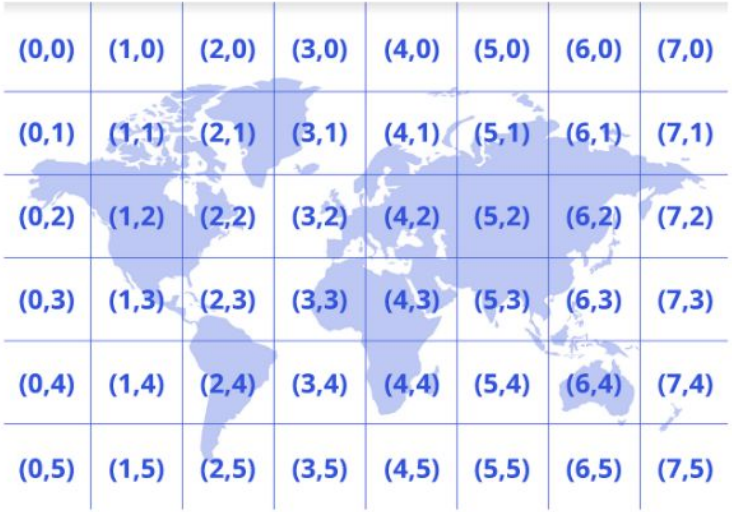
Spatial Indexes

Multi-resolution, hierarchical grids that are “geolocated” by a short reference string, rather than a complex geometry:

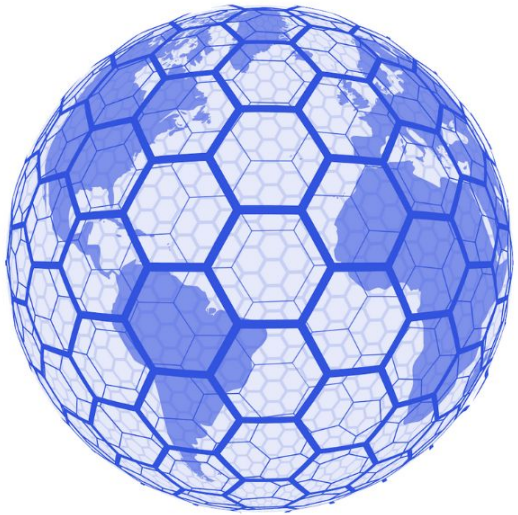
- **EFFICIENCY** → smaller to store, faster to process and more computationally efficient.
- **FLEXIBILITY** → combining datasets into one layer for ease of comparison and analysis.
- **OBJECTIVITY** → remove bias associated with traditional administrative geographies.
- **IMPACT** → visually more impactful and much easier to understand.



Spatial Indexes

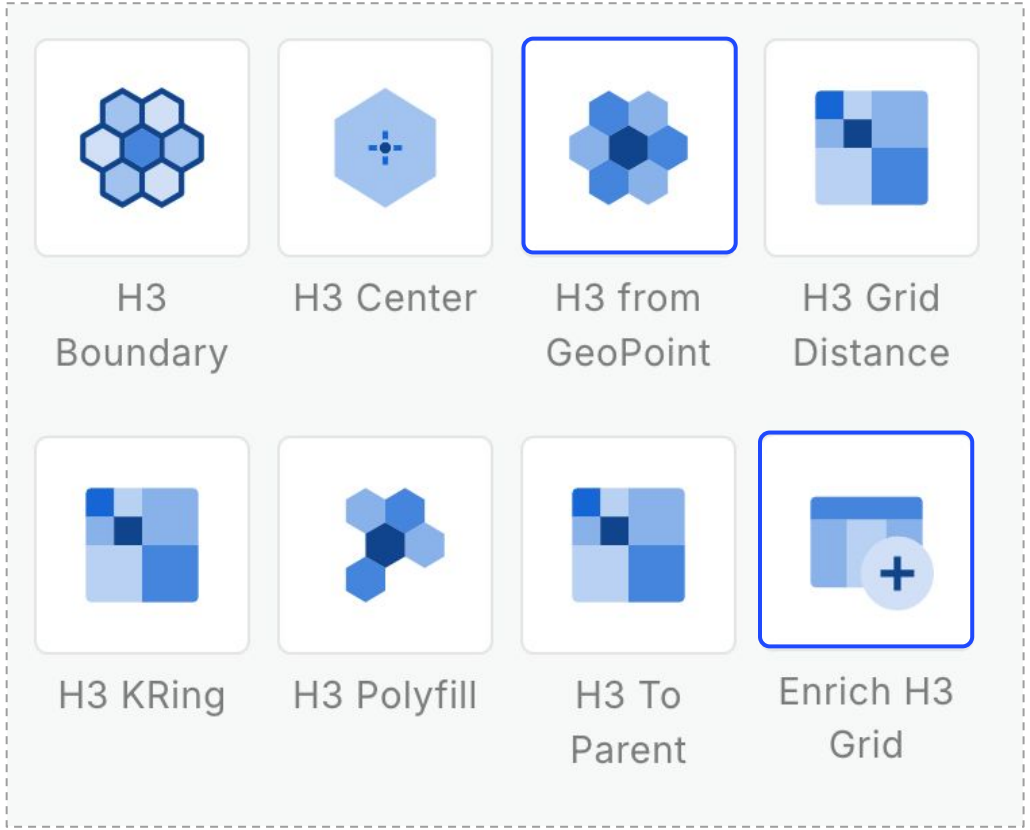


Quadbin



H3

Spatial Indexes Operations



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h3 string	acs_year number	total_pop_sum number	median_age_avg number	median_rent_avg number	black_pop_sum number	hispanic_pop_sum number	owner_occupied_housing_units_median_value_sum number	vacant_housing_units_sum number	housing_units_sum number	families_with_young_children_sum number	urbanity_any string	urbanity_any_ordinal number
872759343ffffff	2,020	307.795	33.3	1,010	15.025	213.888	47,903.738	5.745	99.431	23.643	rural	0
872759343ffffff	2,011	242.27	34.5	912	7.061	164.382	42,011.061	7.502	83.625	22.727	rural	0
872759343ffffff	2,019	306.248	31.1	978	14.141	209.468	42,733.316	6.187	100.315	16.793	rural	0
872759343ffffff	2,010	238.298	27.9	934	5.075	168.794	41,591.833	7.943	77.006	16.769	rural	0
872759343ffffff	2,007	272.498	26.4	877	16.99	176.076	76,078.855	8.164	89.582	12.797	rural	0
872759343ffffff	2,013	273.381	32.4	941	7.281	193.286	39,716.34	7.723	85.611	23.389	rural	0
872759343ffffff	2,014	288.164	32.1	953	0	214.027	38,723.431	4.413	96.864	22.506	rural	0
872759343ffffff	2,009	278.456	26.7	949	26.257	179.165	63,435.82	12.577	92.671	19.417	rural	0
872759343ffffff	2,008	262.569	26.2	913	15.666	159.969	76,277.437	9.267	82.08	15.004	rural	0
872759343ffffff	2,006	268.306	26.1	850	18.534	183.357	78,042.607	7.723	88.038	20.52	rural	0

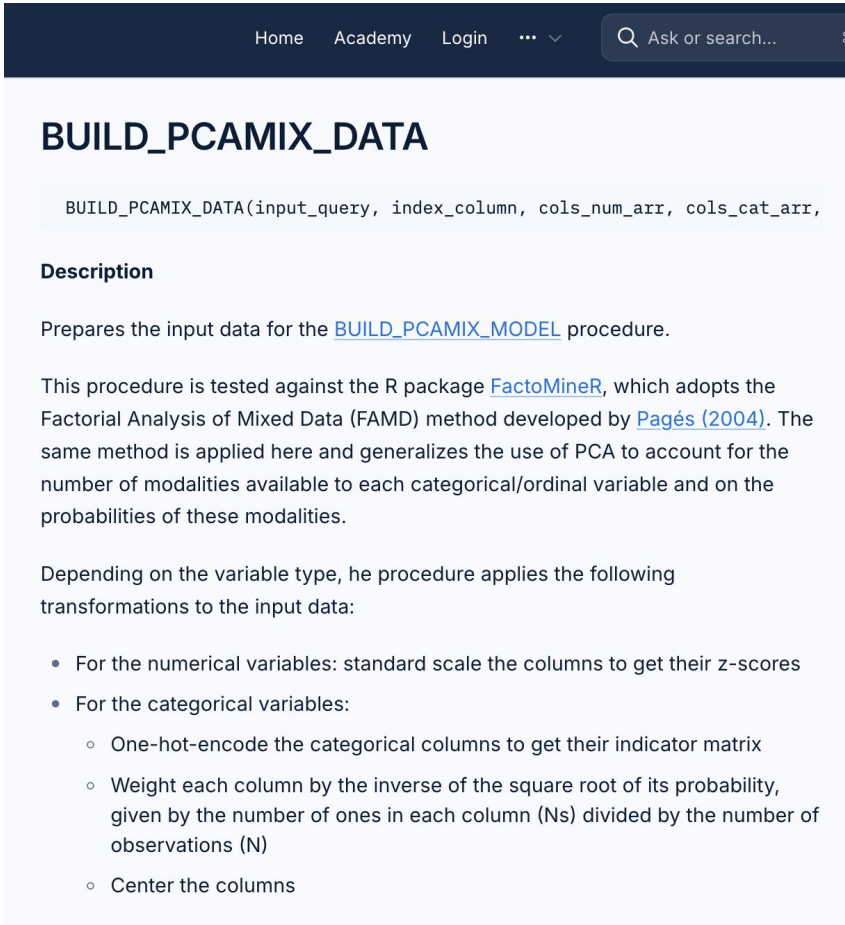
h3 string	acs_year number	principal_component_1 number	principal_component_2 number
872759343ffffff	2,020	2.595	-1.772
872759343ffffff	2,011	2.731	-1.728
872759343ffffff	2,019	2.565	-1.934
872759343ffffff	2,010	2.517	-2.169
872759343ffffff	2,007	2.526	-2.293
872759343ffffff	2,013	2.639	-1.861
872759343ffffff	2,014	2.618	-1.879
872759343ffffff	2,009	2.461	-2.242
872759343ffffff	2,008	2.485	-2.292
872759343ffffff	2,006	2.541	-2.326

11 socio-demo variables → 2 principal components

Factorial Analysis of Mixed data

- **Generalizes the use of PCA** to account for the number of modalities available to each categorical/ordinal variable and on the probabilities of these modalities.

- Depending on the variable type, the procedure applies the **different transformations** to the input data



Factorial Analysis of Mixed data - Categorical

One-hot encoding

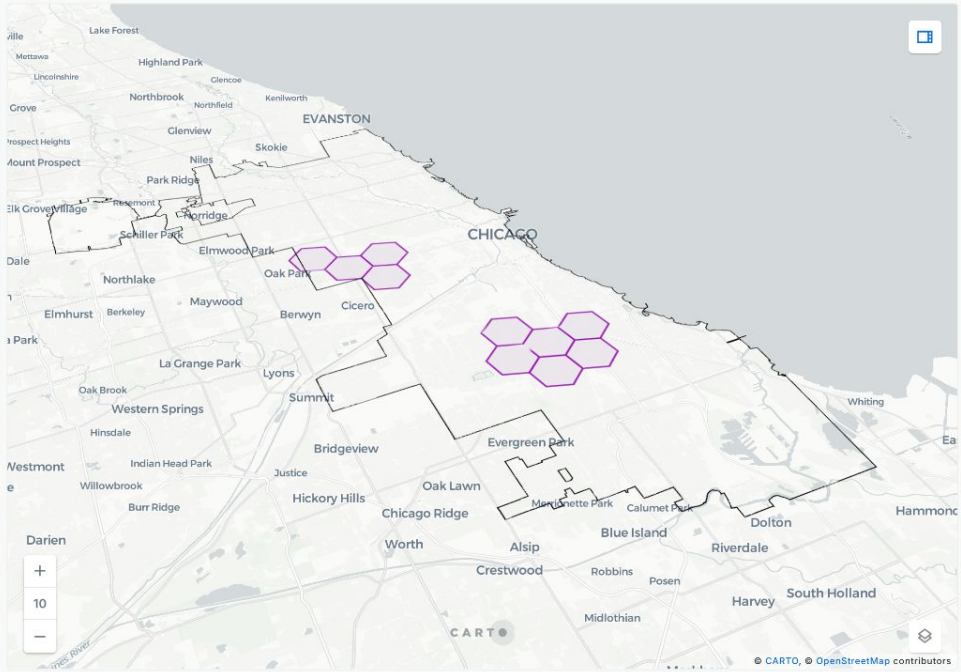
- Converts categorical variables into a binary format
- Ensures that each category is treated independently, preventing the PCA from mistakenly assuming any sort of ordinal relationship

Weighting

- Weight each OHE column by the inverse of the square root of its probability
- Ensures that less frequent categories, which may still carry meaningful information, are given more importance

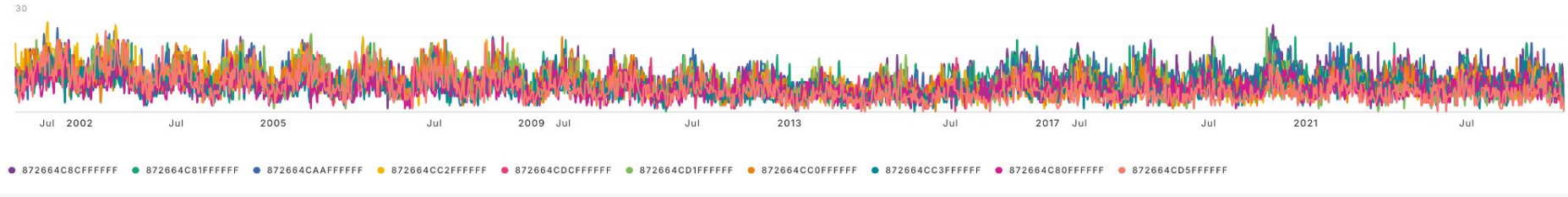
Centering

- Zero-center the data (subtracting the column mean)
- Makes sure that all features have a mean of 0 to avoid bias.



Violent crime counts (Top 10 H3 cells)

01/01/2001 - 30/12/2024

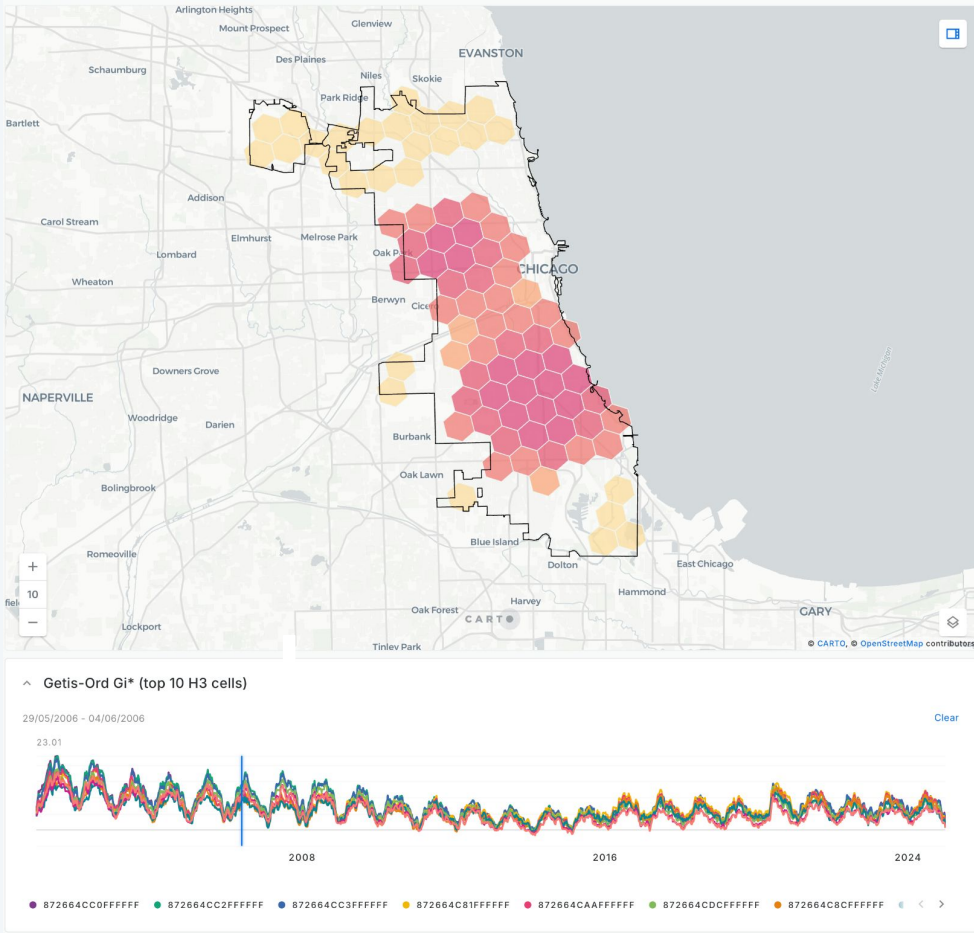


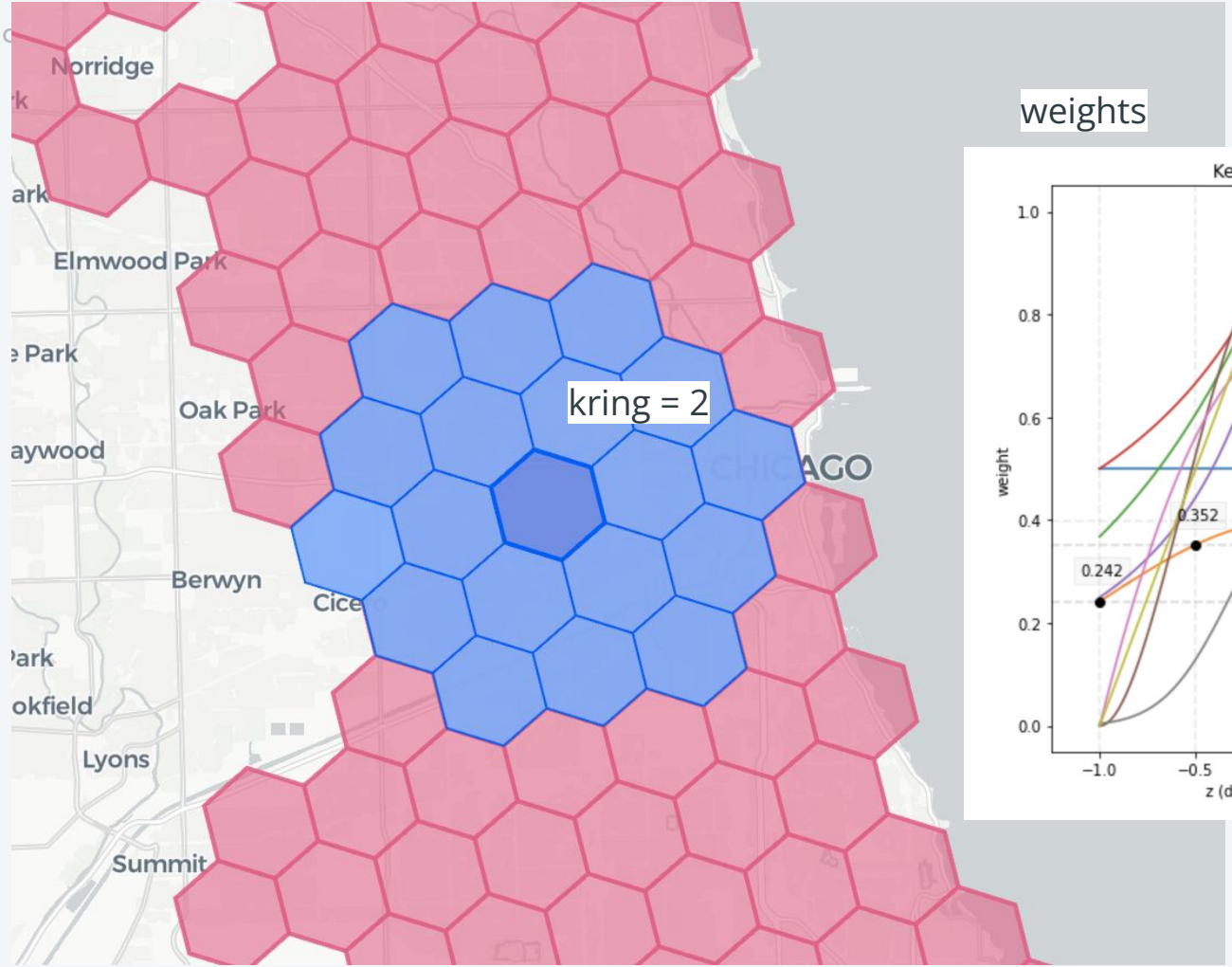
Exploratory Analysis: space-time insights

Hotspot classification

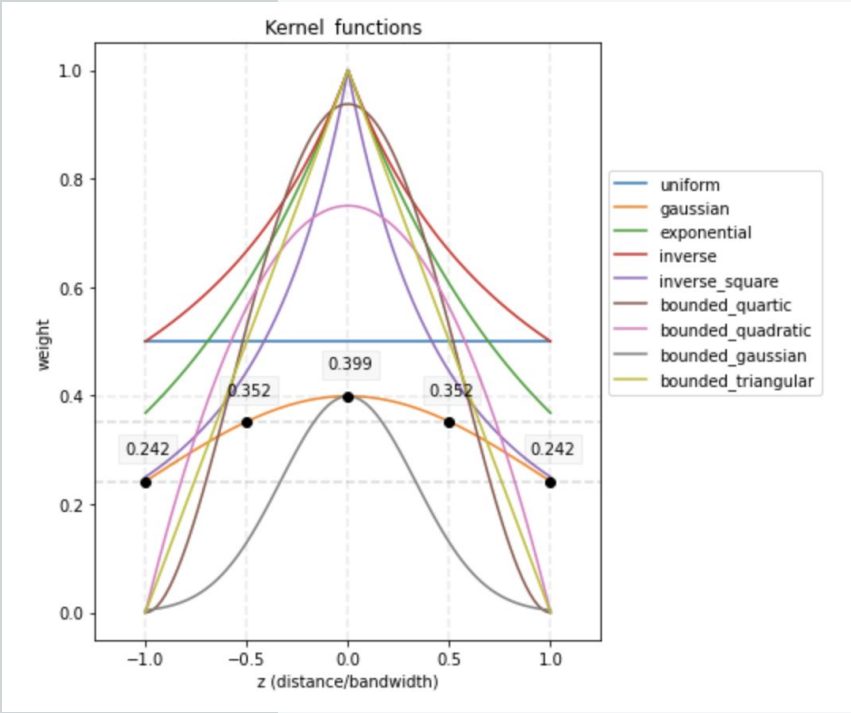
Space-time Getis-Ord

- **Identifies hot and cold spots:** high positive Z-scores indicate hot spots, while low negative Z-scores indicate cold spots.
- Allows to **compare space-time patterns**:
    - Summer vs Winter
    - 2021 vs 2022



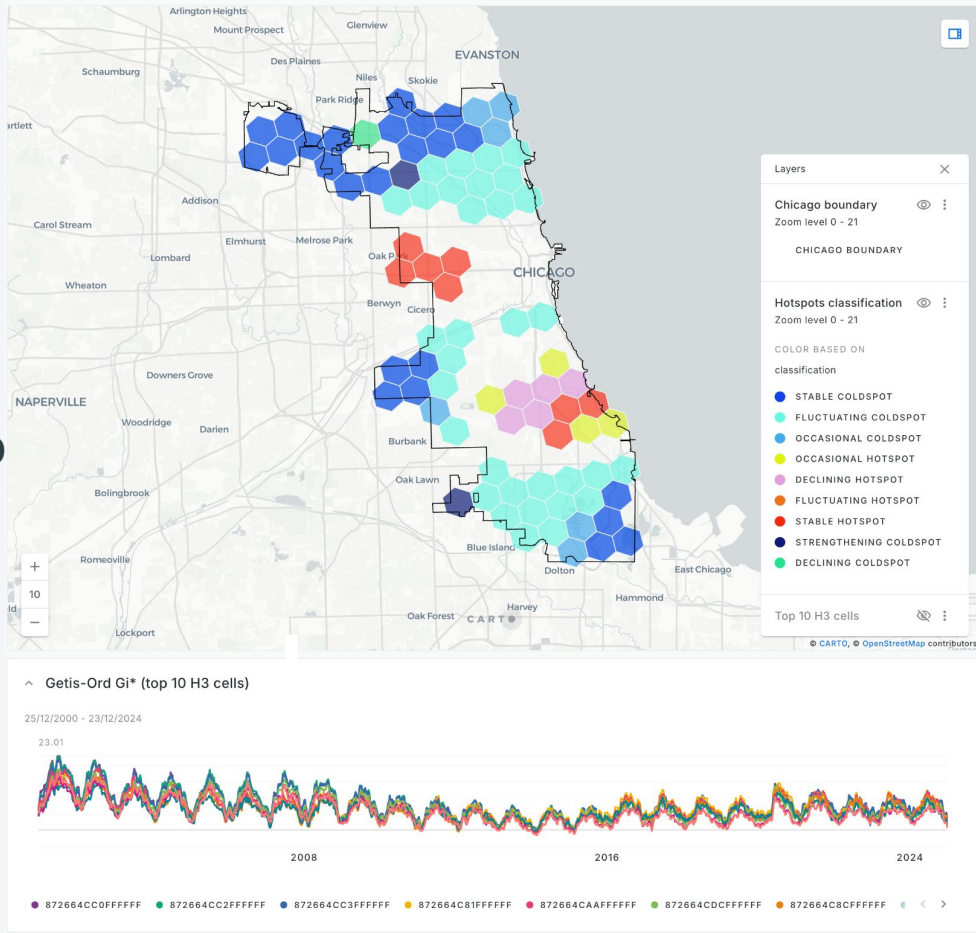

Norridge
Elmwood Park
Oak Park
Berwyn
Lyons
Summit
kring = 2

weights

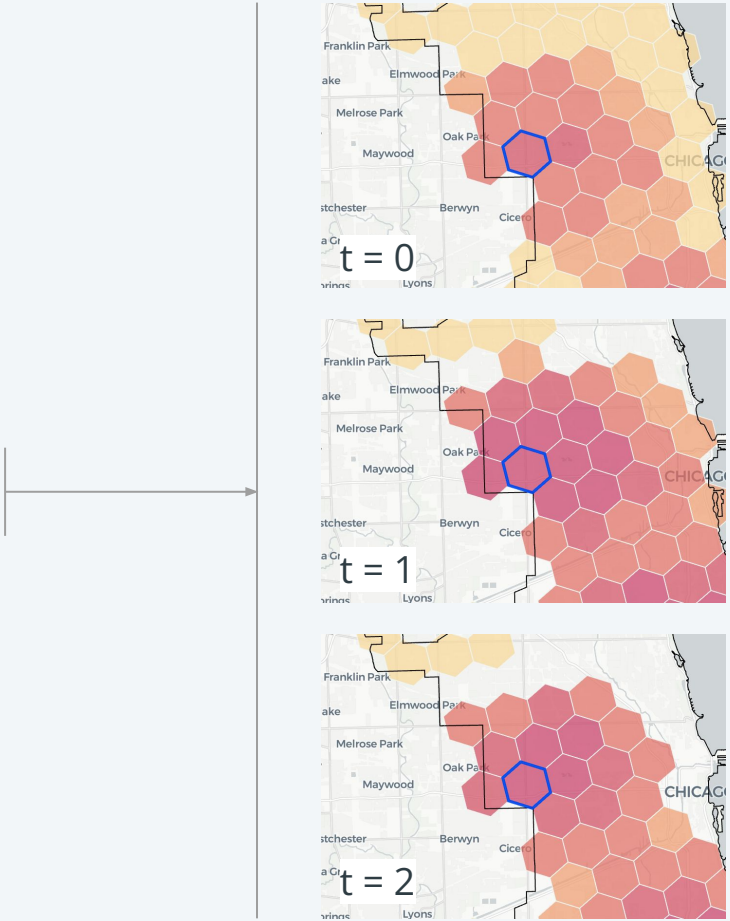

Kernel functions
weight
z (distance/bandwidth)
0.399
0.352
0.352
0.242
0.242
uniform
gaussian
exponential
inverse
inverse_square
bounded_quartic
bounded_quadratic
bounded_gaussian
bounded_triangular

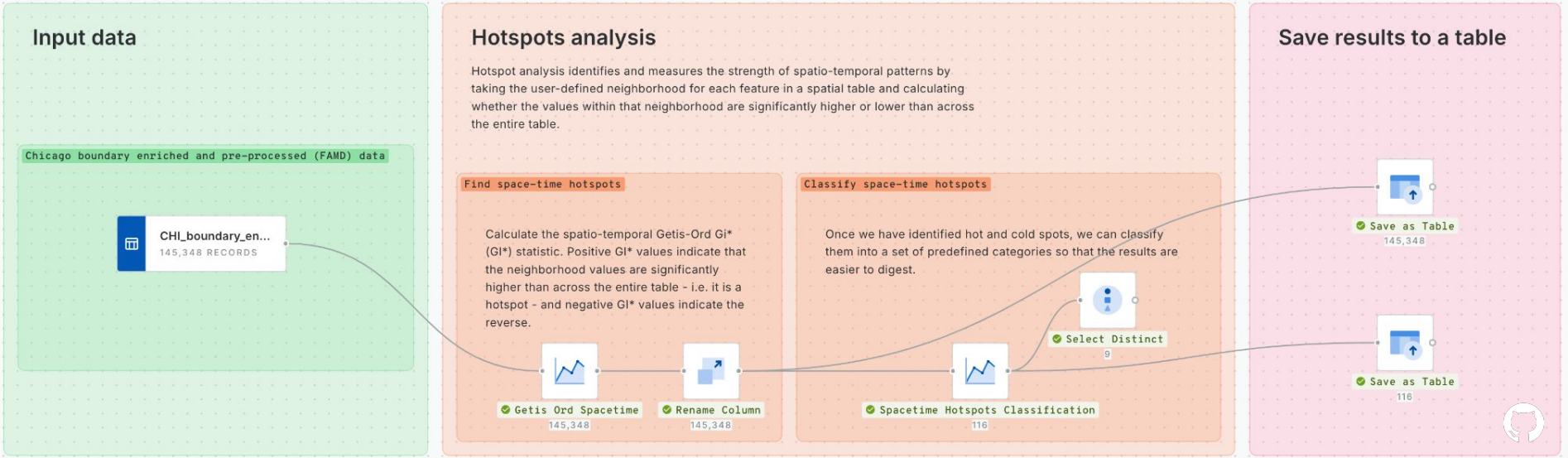
Hotspot Classification

- Serves as **a digest of space-time Getis-O**
- Will collapse Gi time series to a set of predefined **categories**
    - West Garfield Park: stable hotposts
    - Suburban villages: coldspots
    - Englewood: declining hotposts?



Category	Description
`Undetected Pattern`	This category applies to locations that do not exhibit any discernible patterns of hot or cold activity as defined in subsequent categories.
`Incipient Hotspot`	This denotes a location that has become a significant hotspot only in the latest observed time step, without any prior history of significant hotspot activity.
`Sequential Hotspot`	Identifies a location experiencing an unbroken series of significant hotspot activity leading up to the most recent time step, provided it had no such activity beforehand and less than 90% of all observed intervals were hotspots.
`Strengthening Hotspot`	A location consistently identified as a hotspot in at least 90% of time steps, including the last, where there's a statistically significant upward trend in activity intensity.
`Stable Hotspot`	Represents a location maintaining significant hotspot status in at least 90% of time steps without showing a clear trend in activity intensity changes over time.
`Declining Hotspot`	A location that has consistently been a hotspot in at least 90% of time steps, including the most recent one, but shows a statistically significant decrease in the intensity of its activity.
`Occasional Hotspot`	Locations that sporadically become hotspot, with less than 90% of time steps marked as significant hotspots and no instances of being a significant coldspot.
`Fluctuating Hotspot`	Marks a location as a significant hotspot in the latest time step that has also experienced significant coldspot phases in the past, with less than 90% of intervals as significant hotspots.
`Legacy Hotspot`	A location that isn't currently a hotspot but was significantly so in at least 90% of past intervals.




Input data
Chicago boundary enriched and pre-processed (FAMD) data
CHI_boundary_en...
145,348 RECORDS
Hotspots analysis
Hotspot analysis identifies and measures the strength of spatio-temporal patterns by taking the user-defined neighborhood for each feature in a spatial table and calculating whether the values within that neighborhood are significantly higher or lower than across the entire table.
Find space-time hotspots
Calculate the spatio-temporal Getis-Ord Gi* (GI*) statistic. Positive GI* values indicate that the neighborhood values are significantly higher than across the entire table - i.e. it is a hotspot - and negative GI* values indicate the reverse.
Getis Ord Spacetime
145,348
Rename Column
145,348
Classify space-time hotspots
Once we have identified hot and cold spots, we can classify them into a set of predefined categories so that the results are easier to digest.
Select Distinct
9
Spacetime Hotspots Classification
116
Save results to a table
Save as Table
145,348
Save as Table
116

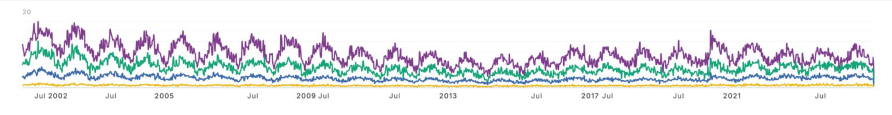
Exploratory Analysis: space-time insights

Time-series clustering

Time Series Clustering

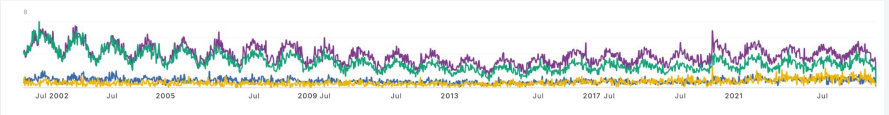
Value characteristic

- Clustering based on **step-by-step distance of the time series values**
  - K-Means with **Euclidean** distance
- The closer the **signals**, the higher the chance of being clustered together



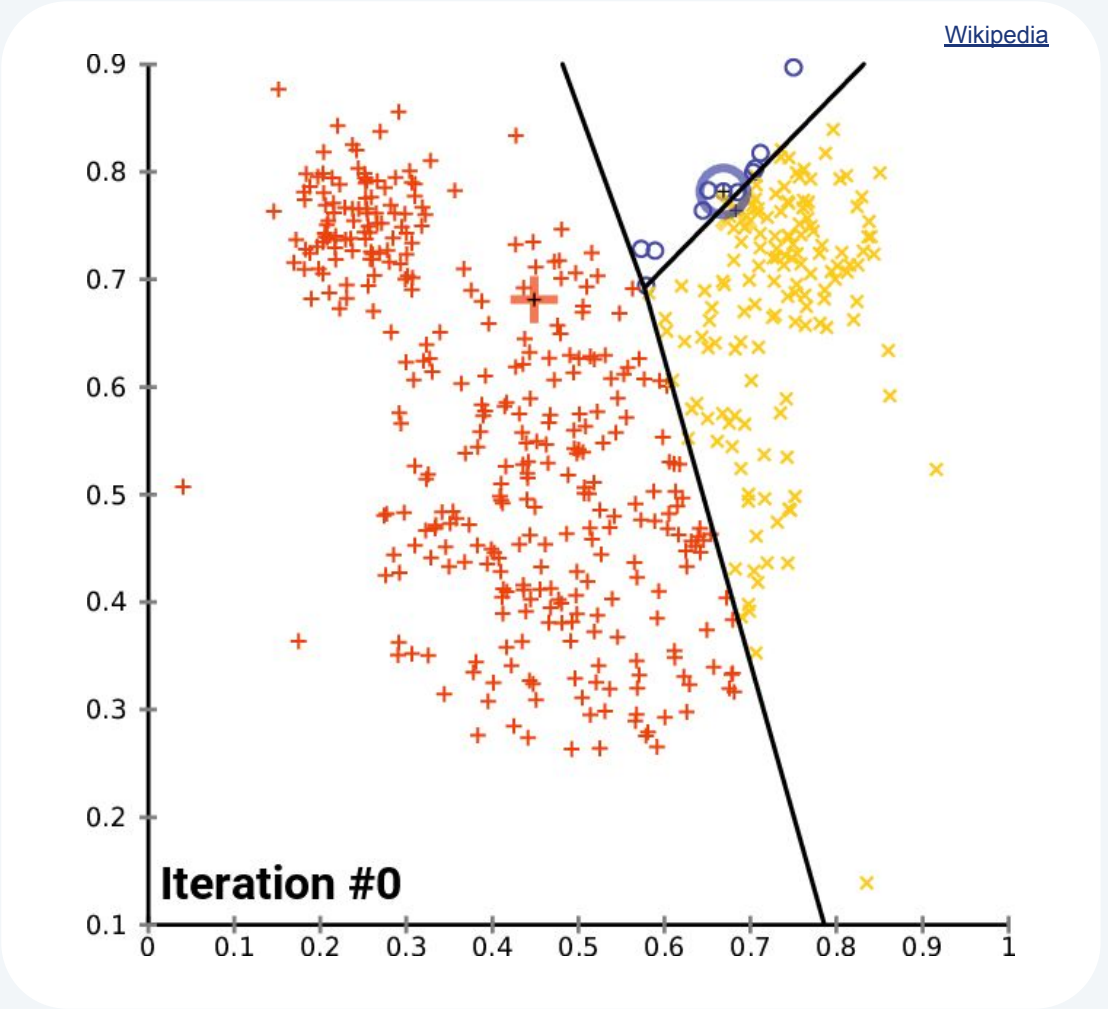
Profile characteristic

- Clustering based on the time series **dynamics** along the timespan passed
  - K-Means with **Cosine** distance
- The closer the **correlation**, the higher the chance of being clustered together

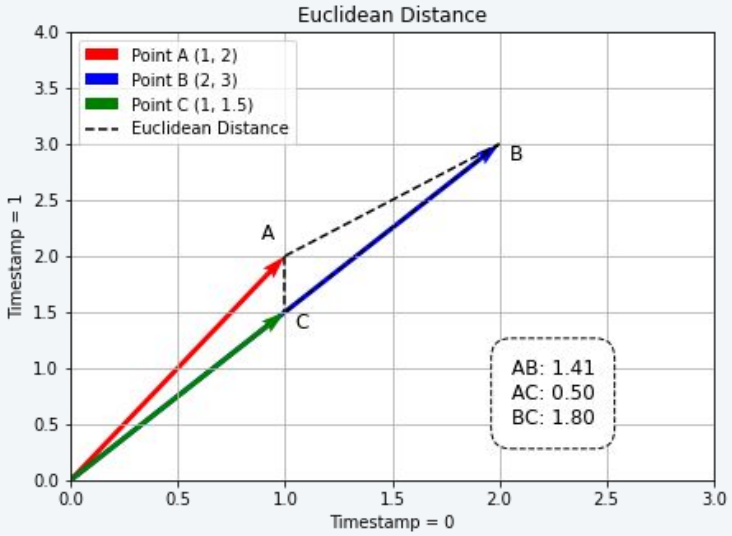


K-means clustering

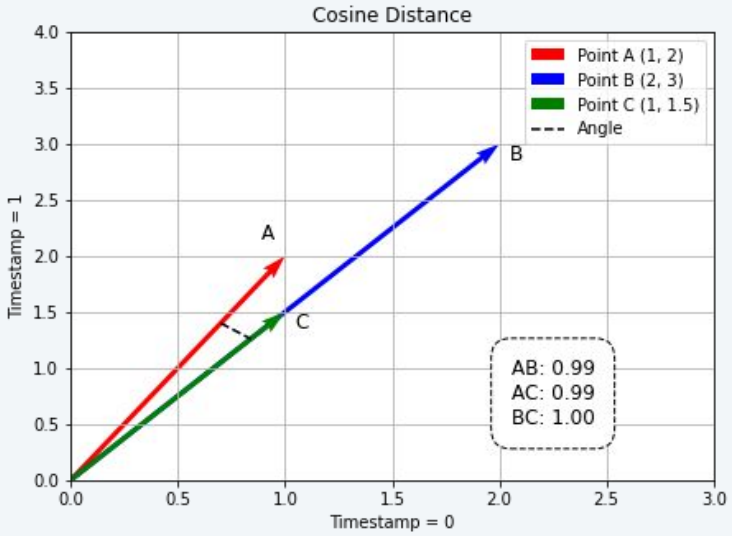
- **Unsupervised learning** algorithm that groups data into K clusters based on their **similarity**
- **Goal**: minimize the variance within each cluster, ensuring that similar points are grouped together
- It starts by randomly selecting K cluster centers (centroids), then **iteratively** assigns each data point to the nearest centroid and recalculates it until convergence



Value characteristic



Profile characteristic



Input data

Chicago boundary enriched and pre-processed (FAMD) data

CHI_boundary_en...
145,348 RECORDS

Time series clustering

Time series clustering is a method used to group time series data into clusters based on similarities in their temporal patterns. It aims to find natural groupings among time series, where series within the same cluster are more similar to each other than to those in other clusters.

By value

The series is clustered based on the **step-by-step distance of its values**. One way to think of it is that the closer the signals, the closer the series will be understood to be and the higher the chance of being clustered together.

Cluster Time Series
116

Rename Column
116

By profile

The series is clustered based on their **dynamics along the time span** passed. This time, the closer the correlation between two series, the higher the chance of being clustered together.

Cluster Time Series
116

Rename Column
116

Join
116

Rename Column
116

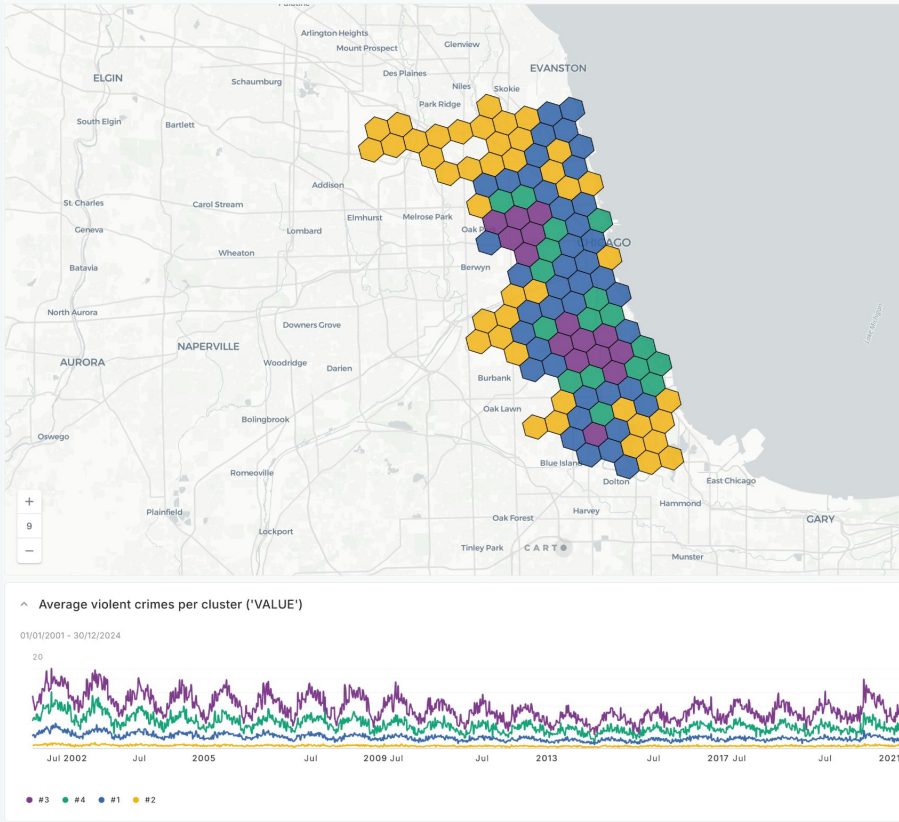
Drop Columns
116

Save results to a table

Save as Table
116

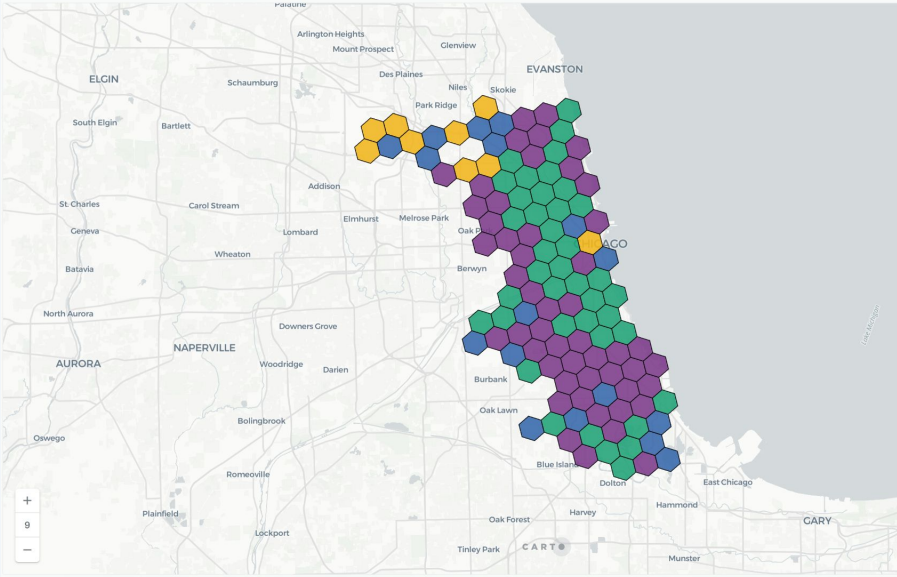
Time Series Clustering - Value

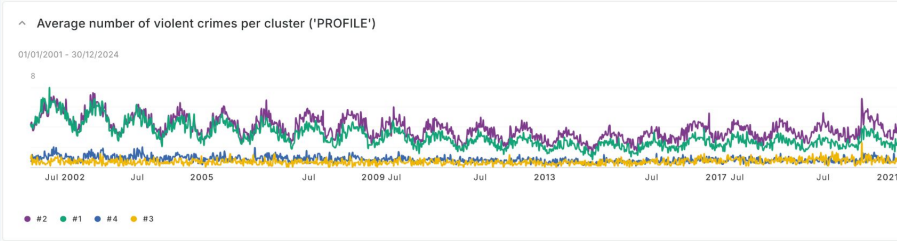
- The closer the **signals**, the higher the chance of being clustered together
    - We can clearly identify areas with very different crime levels, from group *purple* with very high-levels to group *yellow* with very low values.



Time Series Clustering - Profile

- The closer the **correlation**, the higher the chance of being clustered together
    - We can identify groups of time series with different seasonalities and trends (e.g. *purple* and *green* are characterized by a large seasonal cycle with different trends, while *yellow* and *blue* do not show any seasonal variability).



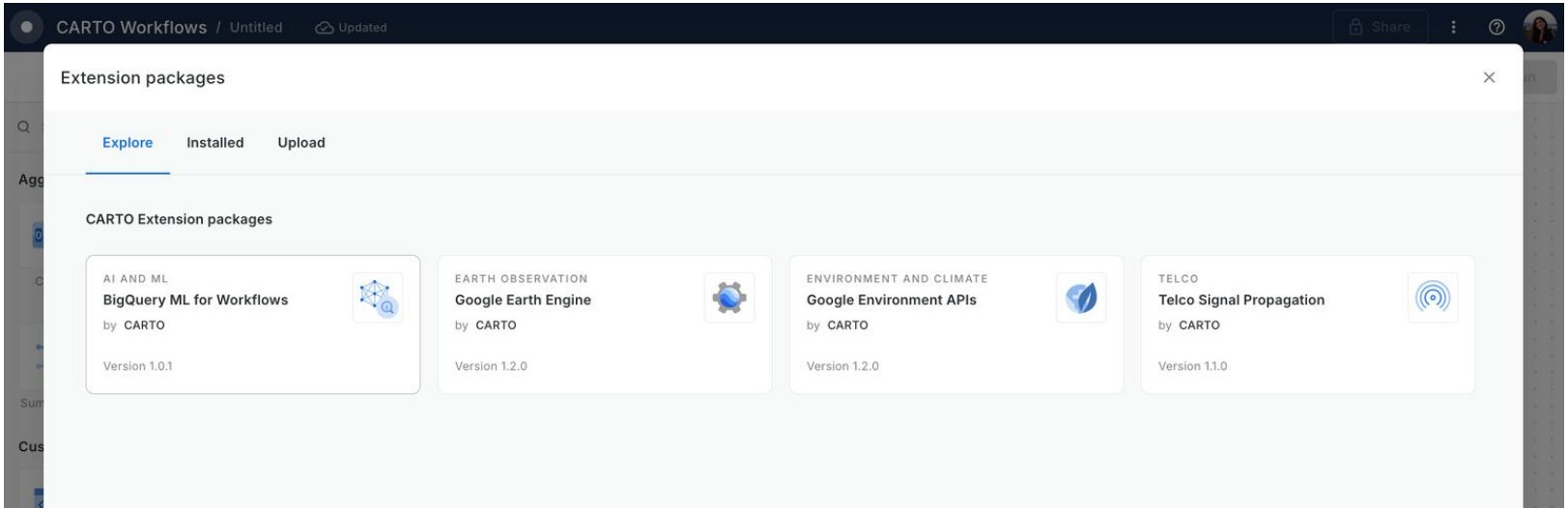


Inferential Analysis

Estimate the expected counts

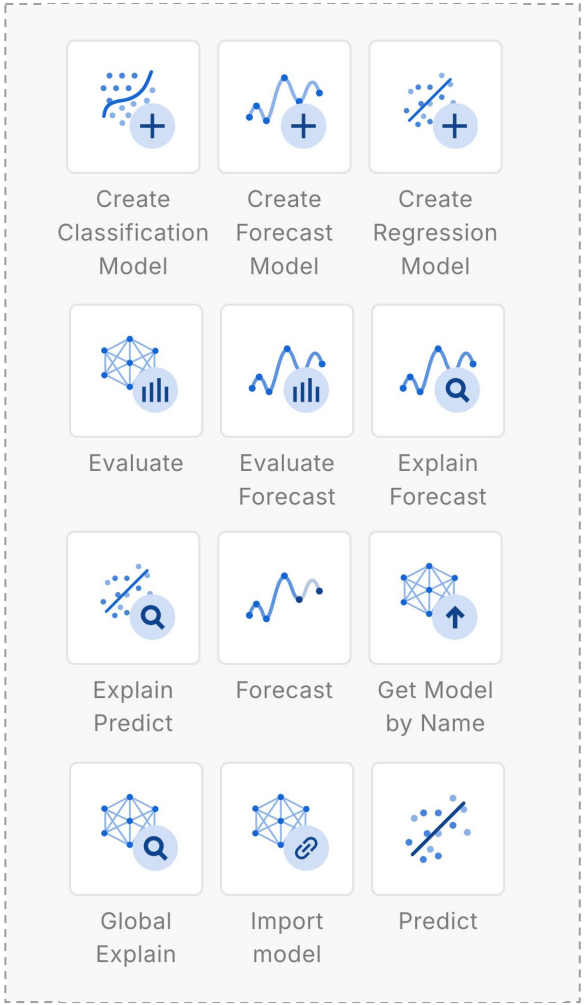
Extension Packages

Workflows Extension Packages is a powerful tool that allows users to extend the functionality of Workflows by creating packages of **custom** components through **SQL** stored procedures, allowing users to **design and integrate components** that are **tailored to** their **specific needs**.



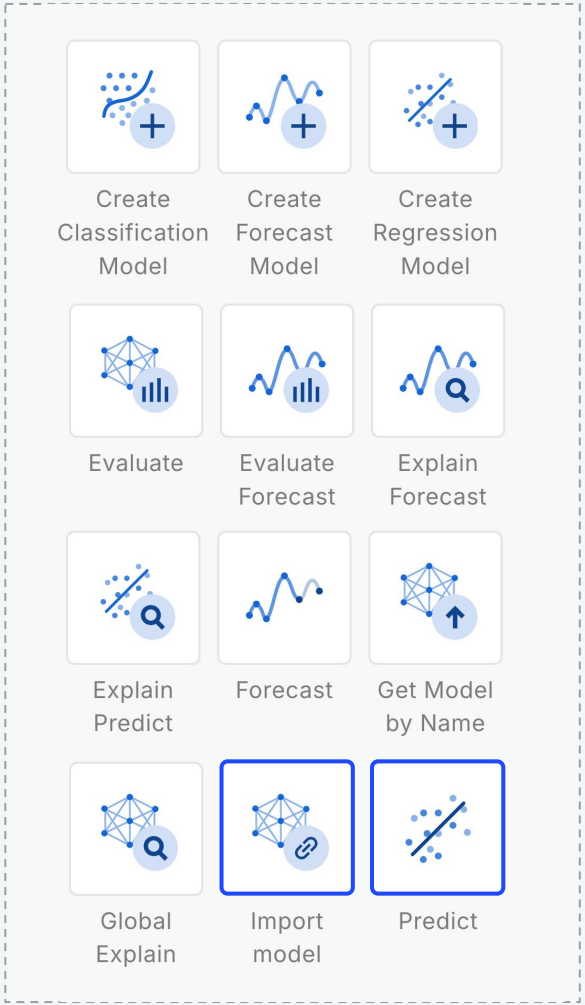
BigQuery ML for Workflows

- Allows users to exploit BigQuery's ML capabilities directly from Workflows, enabling a seamless integration of machine learning models into automated pipelines.
- With minimal coding required, users can quickly build, train, and deploy predictive models using data stored in Google BigQuery.
- All components are created on top of BigQuery ML's capabilities, with each component invoking a specific BQ ML procedure.



We will...

1. Extract and select features from the data
2. Train a model using Python's scikit-learn to estimate the expected crime counts per 1000 people
3. Save the model to ONNX (Open Neural Network Exchange) format
4. Import the model into BigQuery using Workflows
5. Run predictions



Input data

Chicago boundary enriched and pre-processed (FAMD) data

CHI_boundary_en...
149,348 RECORDS

Public Holidays dataset from BigQuery ML datasets

US Public Holidays
800

Create spatial lag variable

We can add spatial-lag variables to account for the influence of neighboring or nearby regions on the variable of interest in a given location. They are derived from the idea that outcomes in one location might not be independent but influenced by outcomes in other nearby locations due to spatial interactions or spillover effects.

$$W_y(i) = \sum_j w_{ij} y_j$$

Select
145,348

H3 KRing
2,761,612

JOIN KRing WITH EACH H3 CEL
2,042,380

COMPUTE THE KRing SUM
145,348

JOIN
145,348

Add temporal lags and seasonal terms

- **Temporal lag variables** are used in time series analysis to account for the effect of past values of a variable on its current or future values. Temporal lags capture the relationship between a variable at one point in time and its previous observations, helping model delayed effects or persistence over time (a.k.a. autocorrelation)
- **Seasonal terms** can be added to model repeating seasonal behaviors. These can be represented as Fourier terms, i.e. as a periodic function by summing sine and cosine functions of different frequencies.

$$\sum_{k=1}^{K} \left[a_k \sin\left(\frac{2\pi k t}{T}\right) + b_k \cos\left(\frac{2\pi k t}{T}\right) \right]$$

ADD TEMPORAL LAGS
145,348

ADD SEASONAL TERMS
145,348

Group by
555

Rename Column
555

Rename Column
555

Join
145,348

Rename Column
145,348

Drop Columns
145,348

Save results to a table

Save as Table
145,348

jupyter train_sklearn_model_onnx_gcs Last Checkpoint: 9 minutes ago (autosaved) Logout

File Edit View Insert Cell Kernel Widgets Help Not Trusted Python 3 (ipykernel)

Run Code

In [3]:
```
import os
import pandas as pd
import numpy as np
from google.cloud import bigquery

%matplotlib inline
from matplotlib import pylab as plt
import matplotlib.dates as mdates
import seaborn as sns

import collections
```

In [4]:
```
## ***********************************************************************************************************************
## BIG QUERY CREDENTIALS
## ***********************************************************************************************************************

bq_client = bigquery.Client.from_service_account_json('my-service-account-key.json')

#!gcloud auth application-default login
#bq_client = bigquery.Client()
```

In [5]:
```
bq_table = 'cartobq.sdsc24_ny_workshops.CHI_boundary_enriched_w_lags'
selected_h3 = '872664c8cffffff'
```

Plotting setup

In [6]:
```
import seaborn as sns
from pandas.plotting import register_matplotlib_converters
register_matplotlib_converters()
```

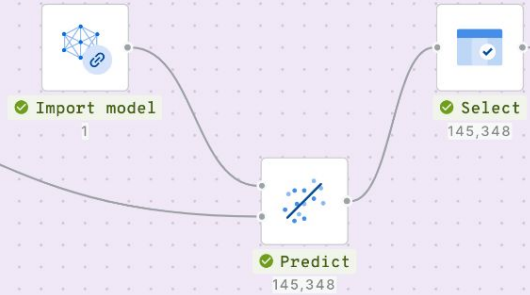
Input data

Chicago boundary enriched and pre-processed (FAMD) data:

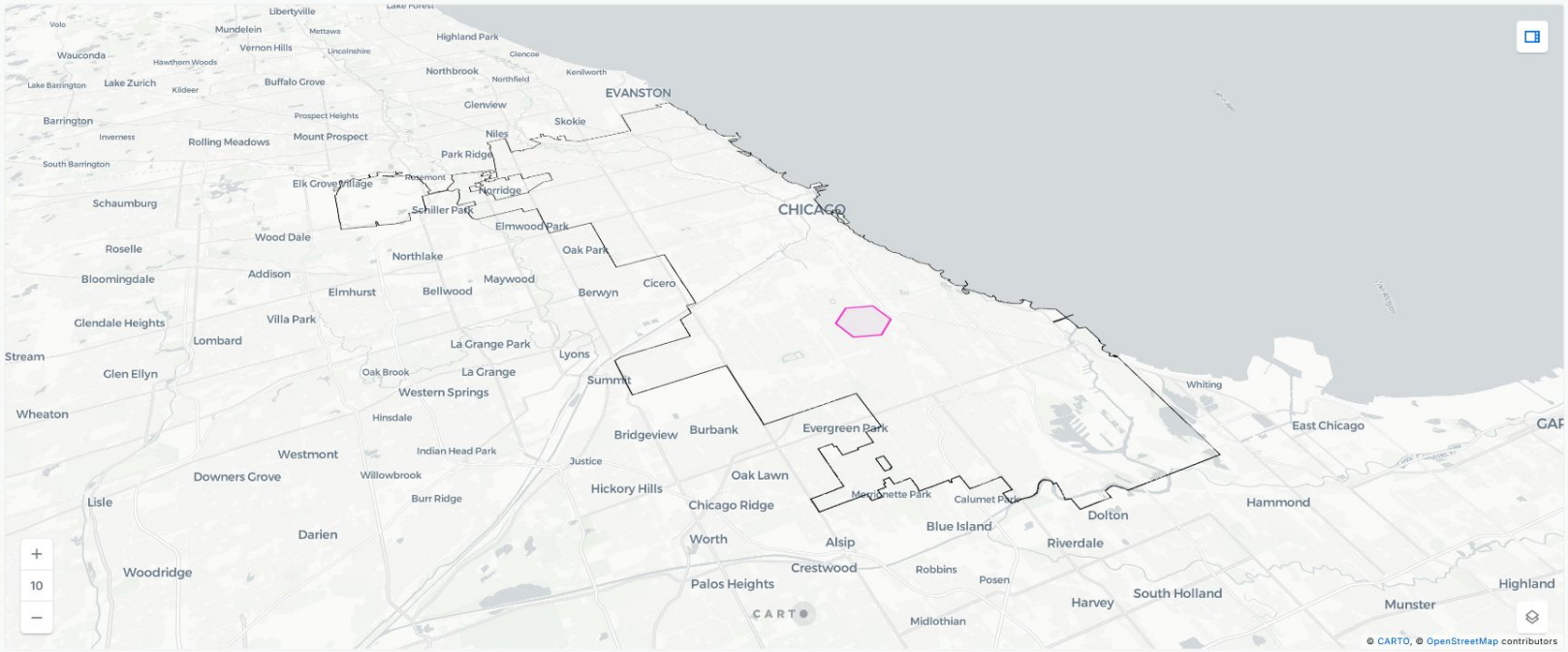
CHI_boundary_en...
145,348 RECORDS

Estimate the expected value of the series conditional on the selected covariates

To estimate the expected crime rate per 1,000 people, we can import a pre-trained model from GCS using scikit-learn. This approach is useful when training and prediction are handled in separate processes (e.g., a data scientist trains the model, while an analyst performs the forecasting) or for specific use cases such as online predictions or predictions based on different data sets.



Save results to a table



Parameters

H3 counts order

Reset

4

Observed and predicted counts

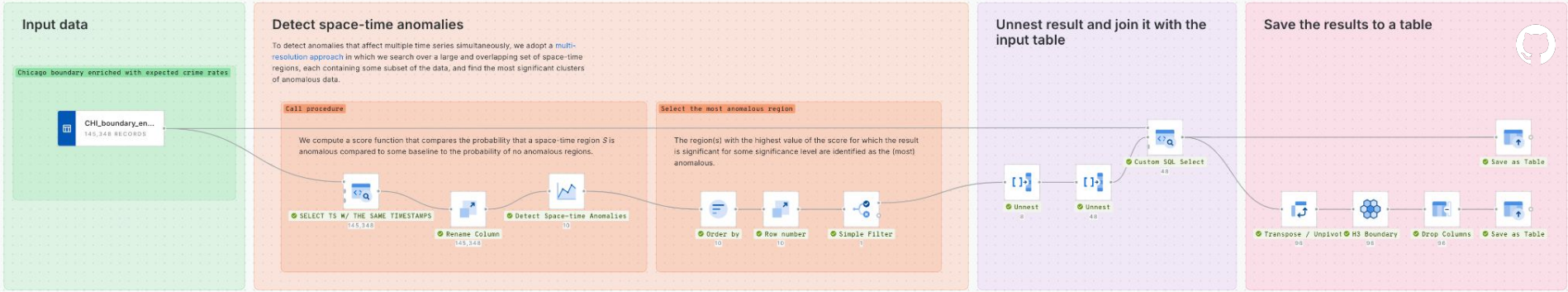
01/01/2001 - 30/12/2024

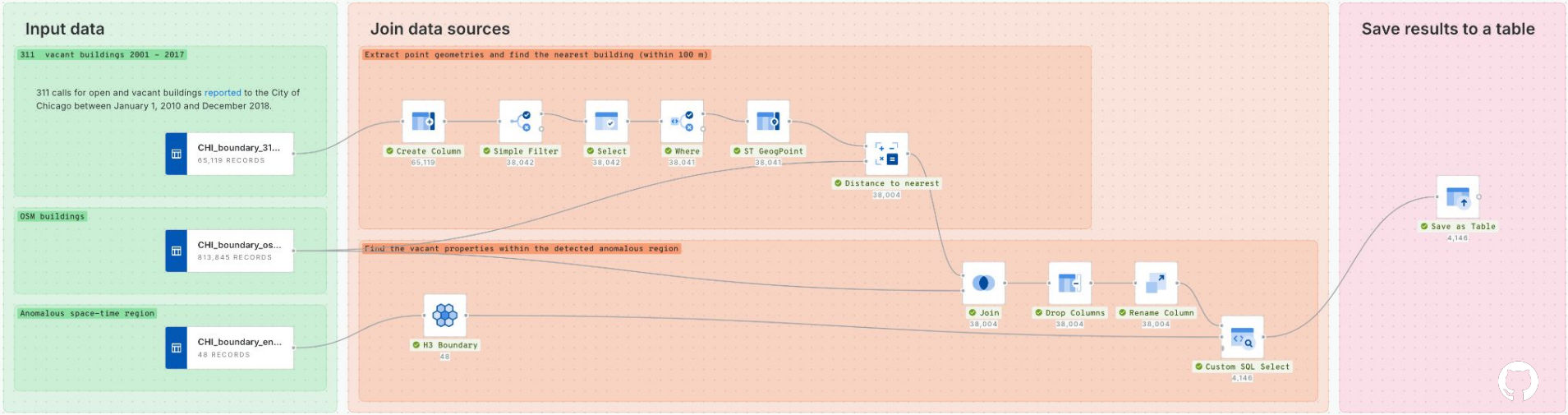
Inferential Analysis

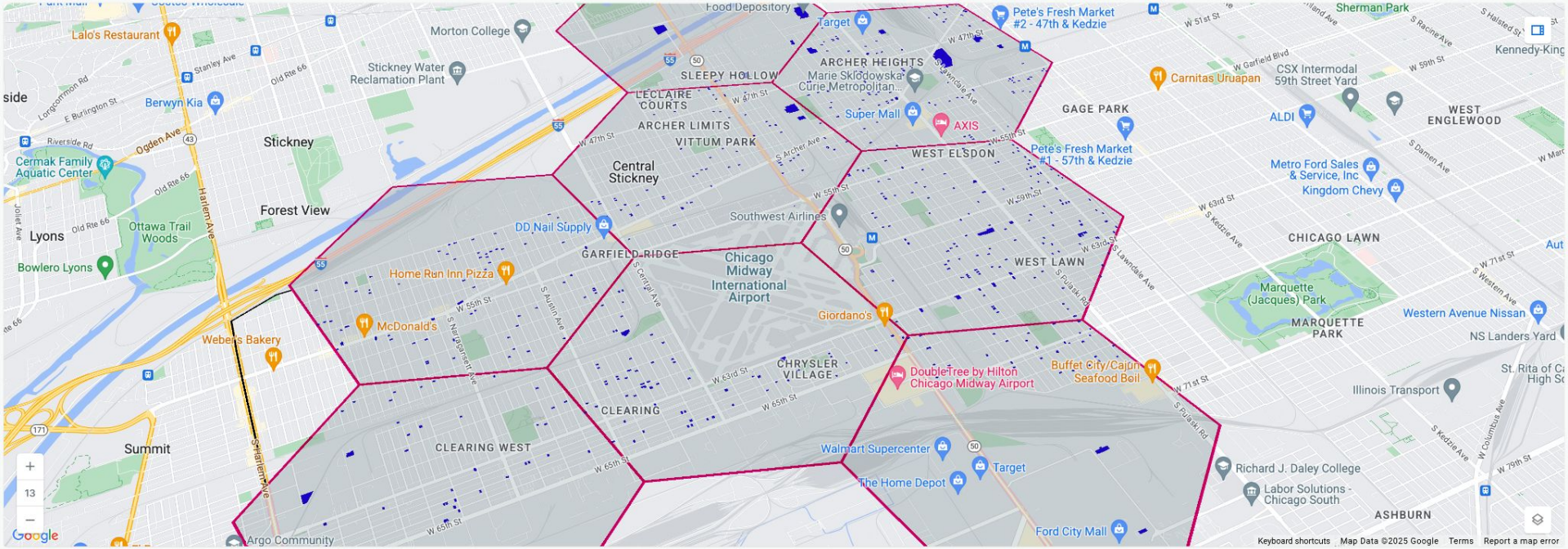
Detect emerging space-time anomalies

Space-time Anomaly Detection

- Based on the **generalized space-time scan statistics framework**:
  - Compute a score function that compares the probability that a space-time region is anomalous compared to some baseline to the probability of no anomalous regions.
  - The region(s) with the highest value of the score for which the result is significant for some significance level are identified as the (most) anomalous.
- Under the null hypothesis of no anomalous space-time regions, we assume **the observed values should be equal to the baseline values** given by the expected counts estimated in the previous section.

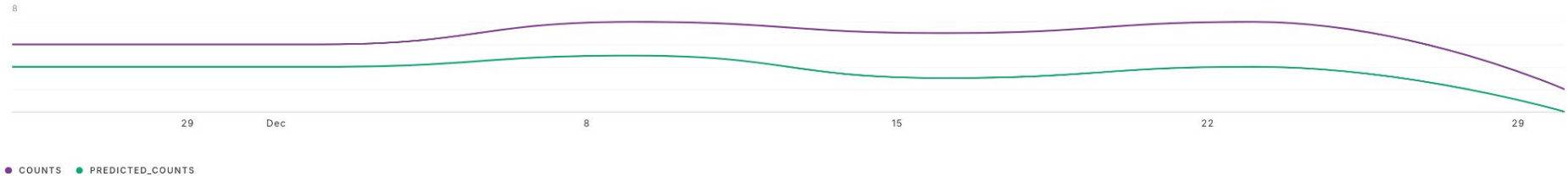

Input data
Chicago boundary enriched with expected crime rates
CHI_boundary_en...
145,348 RECORDS
Detect space-time anomalies
To detect anomalies that affect multiple time series simultaneously, we adopt a multi-resolution approach in which we search over a large and overlapping set of space-time regions, each containing some subset of the data, and find the most significant clusters of anomalous data.
Call procedure
We compute a score function that compares the probability that a space-time region S is anomalous compared to some baseline to the probability of no anomalous regions.
SELECT TS W/ THE SAME TIMESTAMPS
145,348
Rename Column
145,348
Detect Space-time Anomalies
10
Select the most anomalous region
The region(s) with the highest value of the score for which the result is significant for some significance level are identified as the (most) anomalous.
Order by
10
Row number
10
Simple Filter
1
Unnest result and join it with the input table
Unnest
8
Unnest
48
Custom SQL Select
48
Save the results to a table
Save as Table
Transpose / Unpivot
96
H3 Boundary
96
Drop Columns
96
Save as Table


Input data
311 vacant buildings 2001 - 2017
311 calls for open and vacant buildings reported to the City of Chicago between January 1, 2010 and December 2018.
CHI_boundary_31...
65,119 RECORDS
OSM buildings
CHI_boundary_os...
813,845 RECORDS
Anomalous space-time region
CHI_boundary_en...
48 RECORDS
Join data sources
Extract point geometries and find the nearest building (within 100 m)
Create Column
65,119
Simple Filter
38,042
Select
38,042
Where
38,041
ST GeogPoint
38,041
Distance to nearest
38,004
Find the vacant properties within the detected anomalous region
H3 Boundary
48
Join
38,004
Drop Columns
38,004
Rename Column
38,004
Custom SQL Select
4,146
Save results to a table
Save as Table
4,146



Observed VS. baseline counts

25/11/2024 - 30/12/2024



Closing thoughts


CARTO
Thanks!
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