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Line Simplification for Efficient Approximate Join Queries On Big Geospatial Data

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Outline

- Introduction
  - Background & Motivations
  - Spatial data challenges & requirements
    - Spatial join
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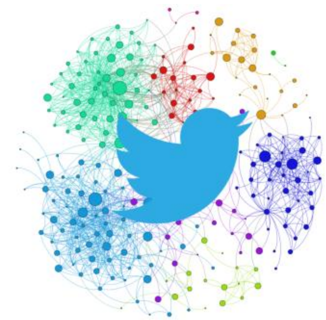
  - Deployment: baselines & testing setup
  - Approximate spatial join Vs. baseline
- Summary & future research

Big data examples

- YouTube : Several petabytes (~**350 PB** of data in 2019)
- **500-700** million **tweets** a day,
  - which adds up to roughly **12 terabytes** of data every 24 hours.
- **Facebook**
  - on the verge of **500** daily **terabytes**,

Source: Forbes



Tweet with exact location

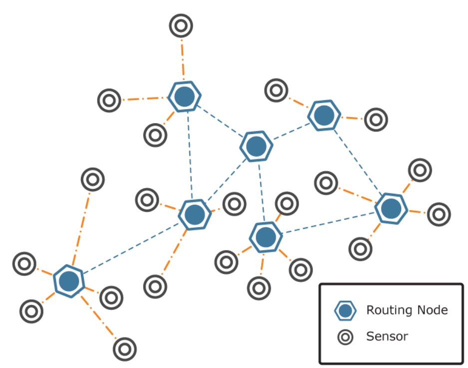

```
{
 "geo" : {
   "type" : "Point" ,
   "coordinates" : [
     40.74118764 ,
     -73.9998279
   ]
 } ,
```


- Most data (>60%) is **geo-referenced**!

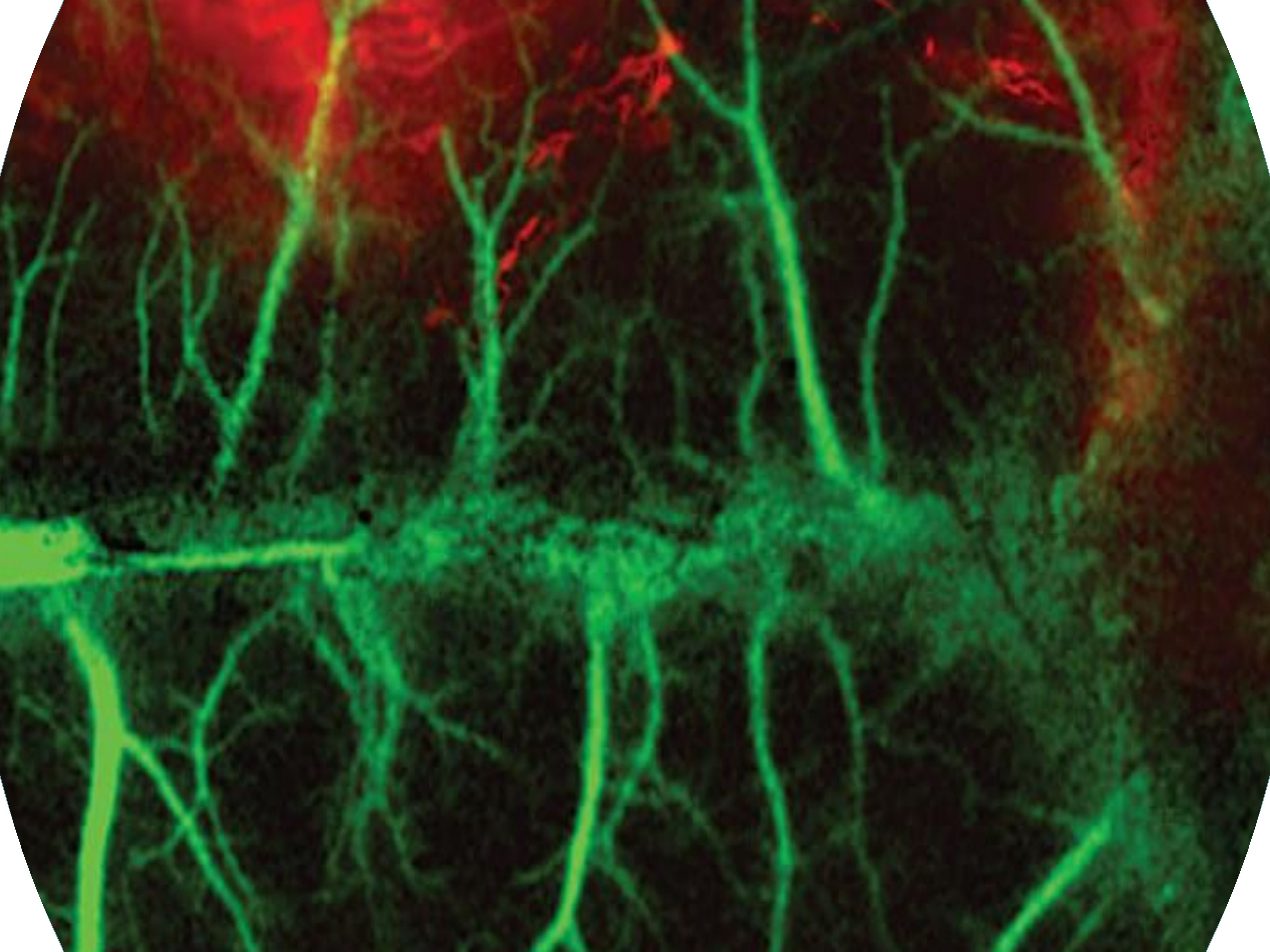
Geospatial Data is everywhere!

Location-based Services

IoT Projects & Sensor Networks



Social Media



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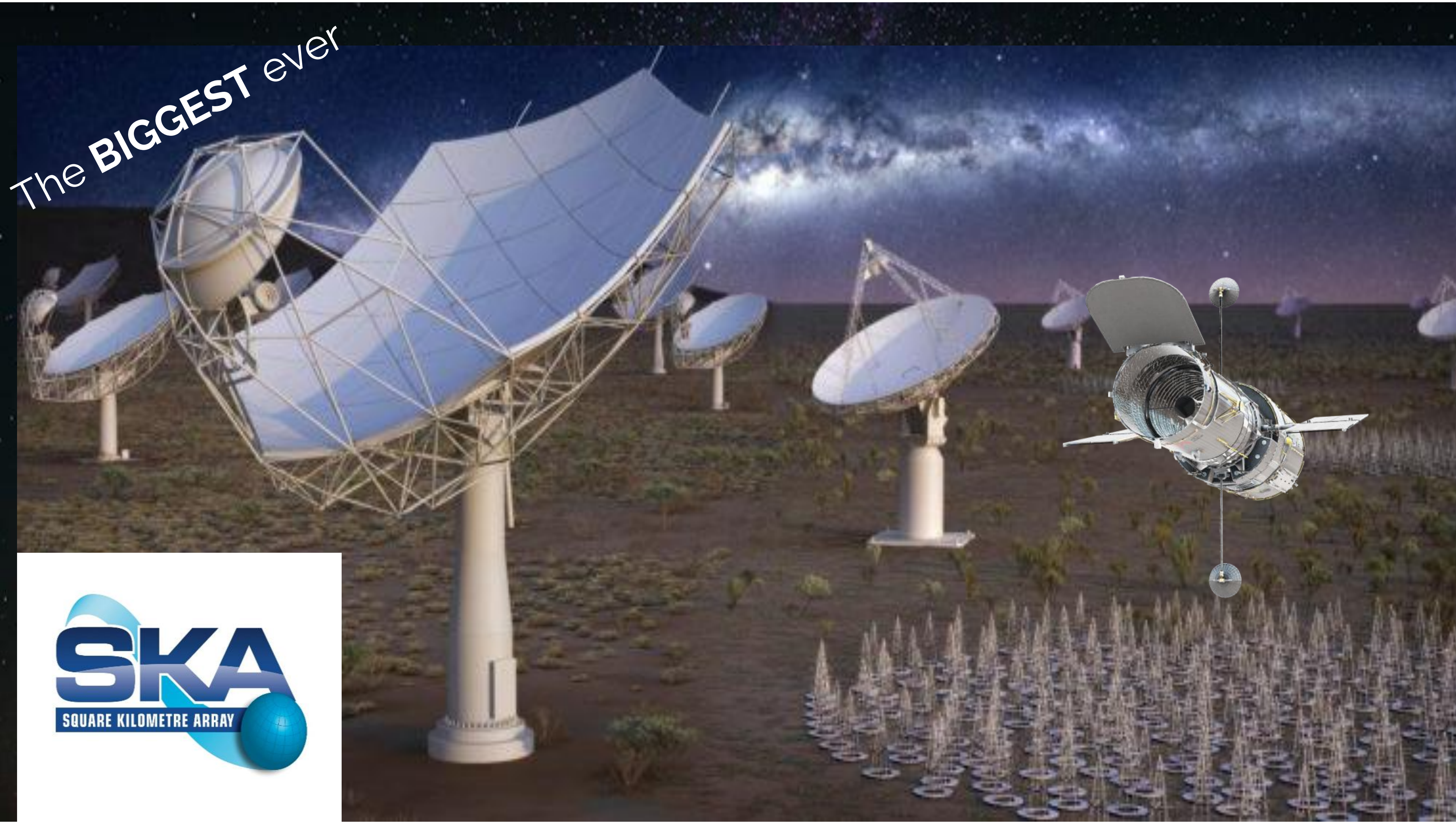

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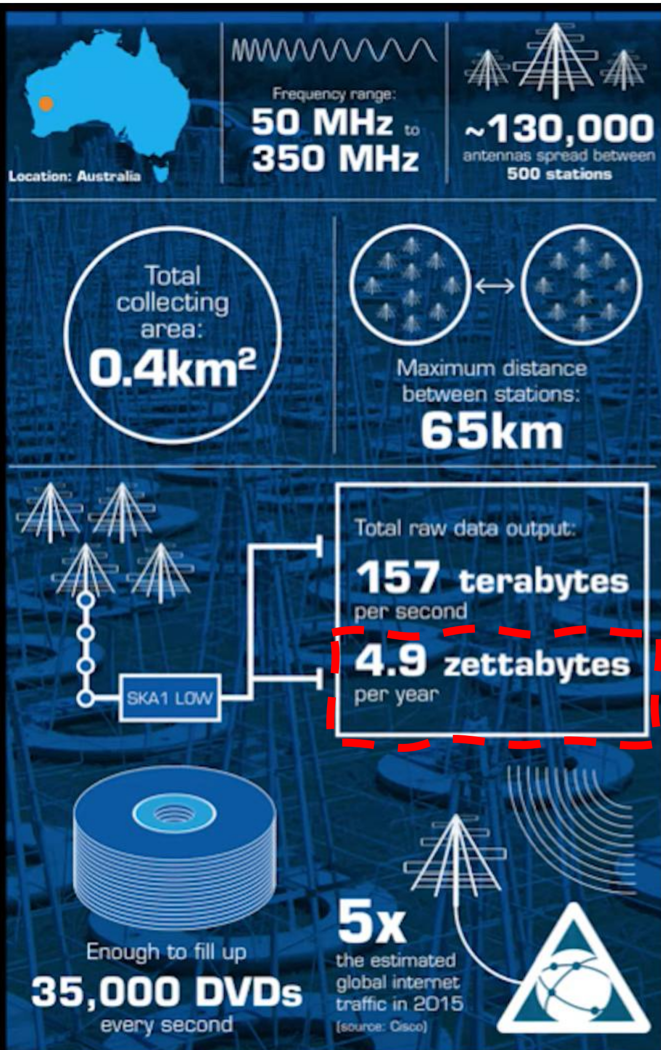
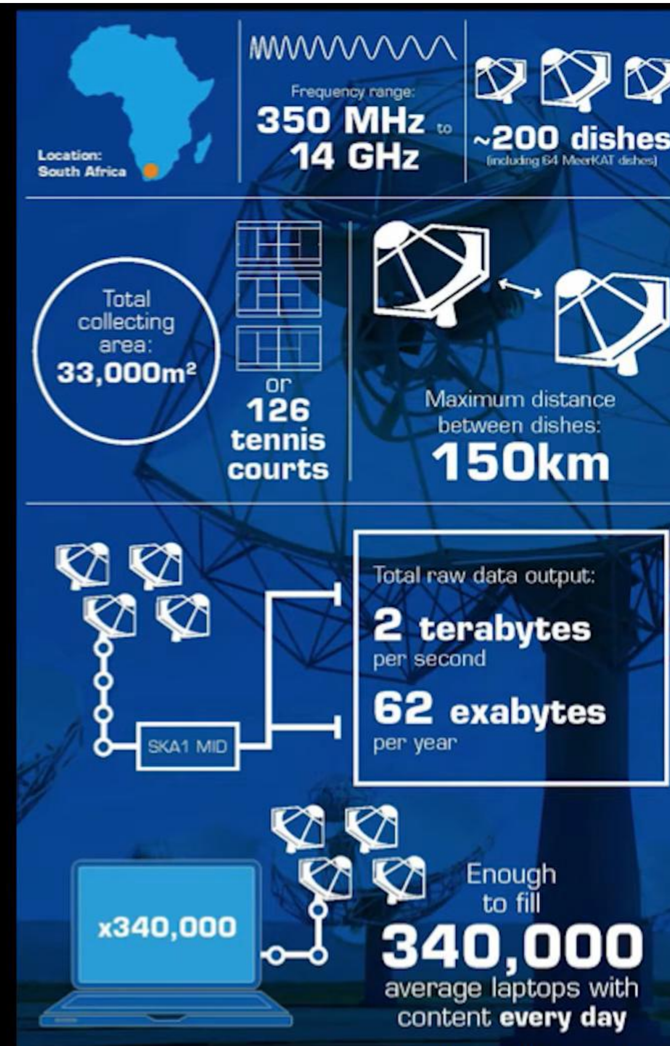


97 ZB of Global digital data was created up to 2022



Courtesy: SKAO, modifications by MJ-H

Spatial Data-intensive applications

- Spatial Data is the primary **challenge**
  - **Volume (size)**,
  - **Complexity**,
  - **Speed** of arrival & **change** (**uncertainty**)

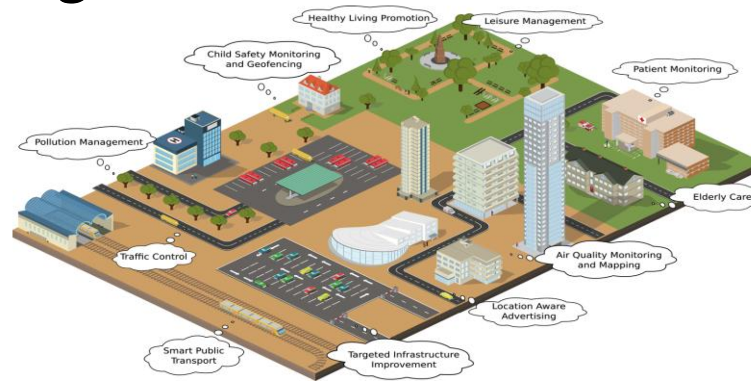
Smart City and Big Data Context

Smart City

Advanced technological services

Geographic Big Data

Huge amount of information

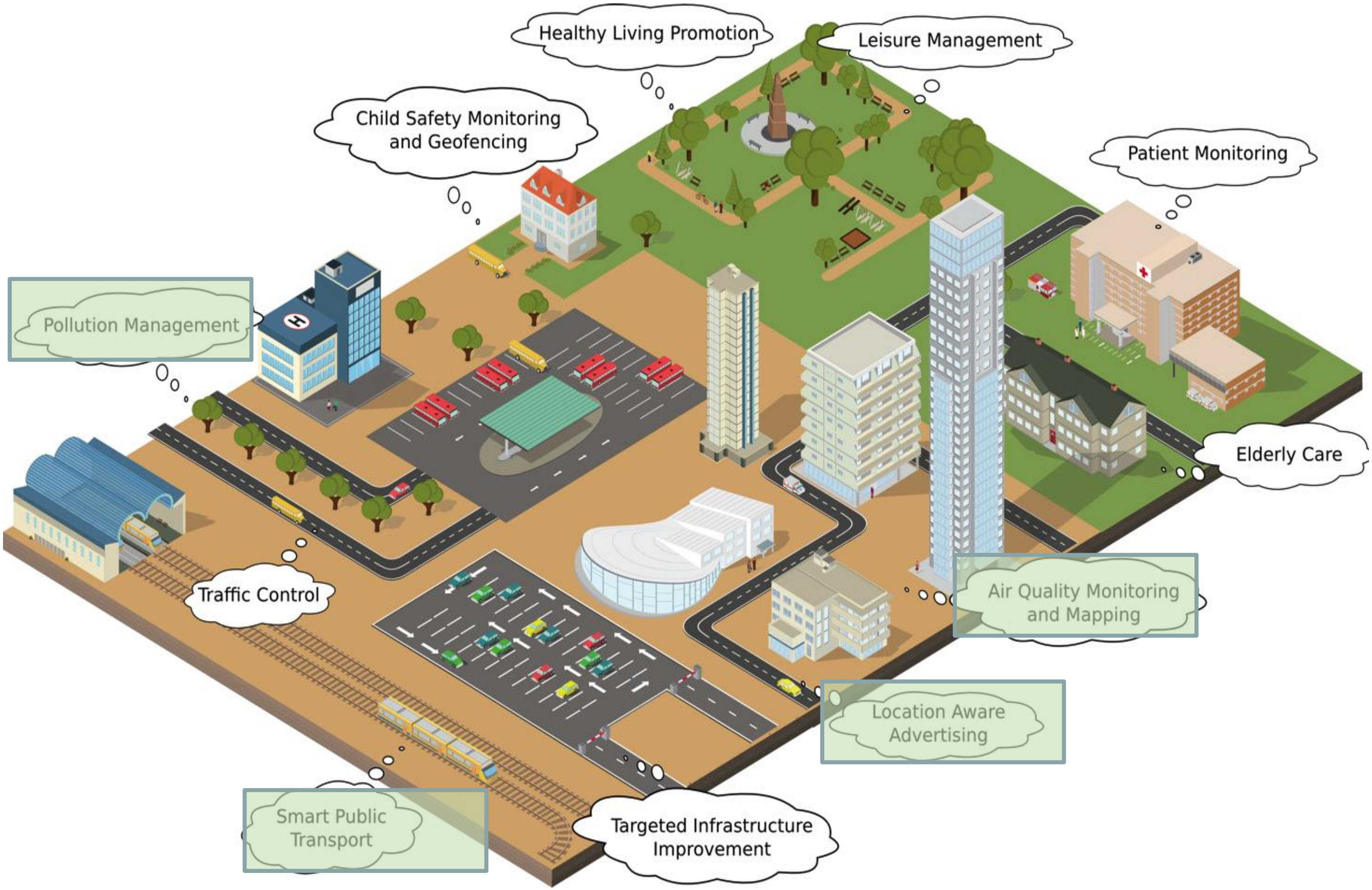


Mobile Sensing

Automatic collection of data

Billions of GPS-enabled handheld devices collect massive data amounts

Location-based services



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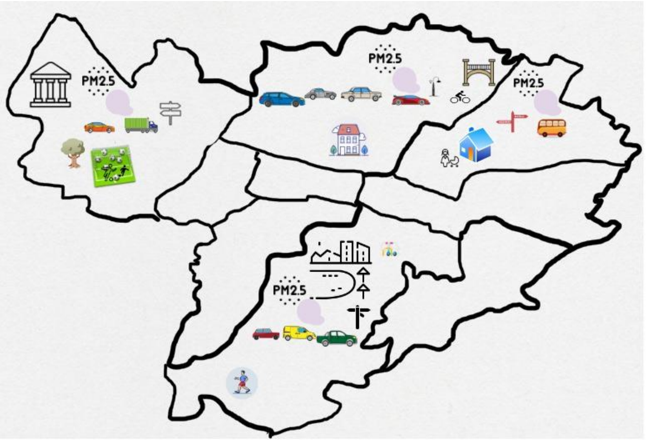
Why Spatial Join?

- Urban Computing
  - Improves **urban environment, human life quality**, and **city operation systems.**
- e.g., **“Planning Bike Lanes based on Sharing-Bike’s Trajectories”**
  - **Spatial join**

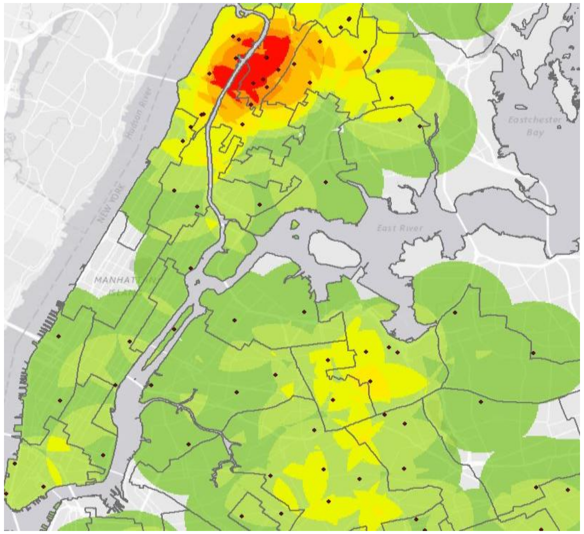


Generating Geo-maps

- Data is subjected to Exploratory Spatial Data Analytics (**ESDA**)
  - Generating geo-maps (e.g., **region-based** maps such as choropleth)
    - Requires **Spatial join** **(costly)**

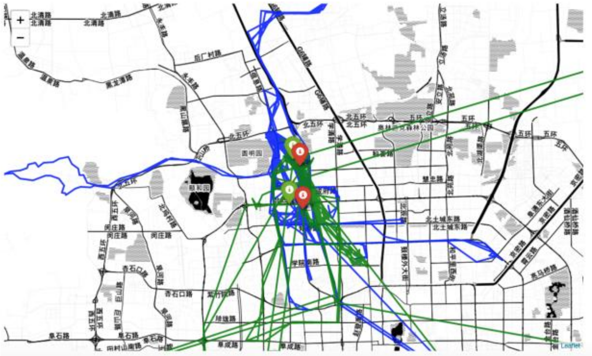


- **Geospatial** aggregation
  - Air pollutants **density** in each **zone**,
  - **Autocorrelation** between nearness and pollution



Visualizing georeferenced data requires aggregation

- **line-based**
  - time-series trajectory visualization of spatial data
  - Requires **aggregations** and **group-by, spatial join**



- **region-based**
  - Tessellating geographic regions into grid cells, then, **grouping** data by region-based **aggregations, requires spatial join**
  - e.g., Choropleth maps generation

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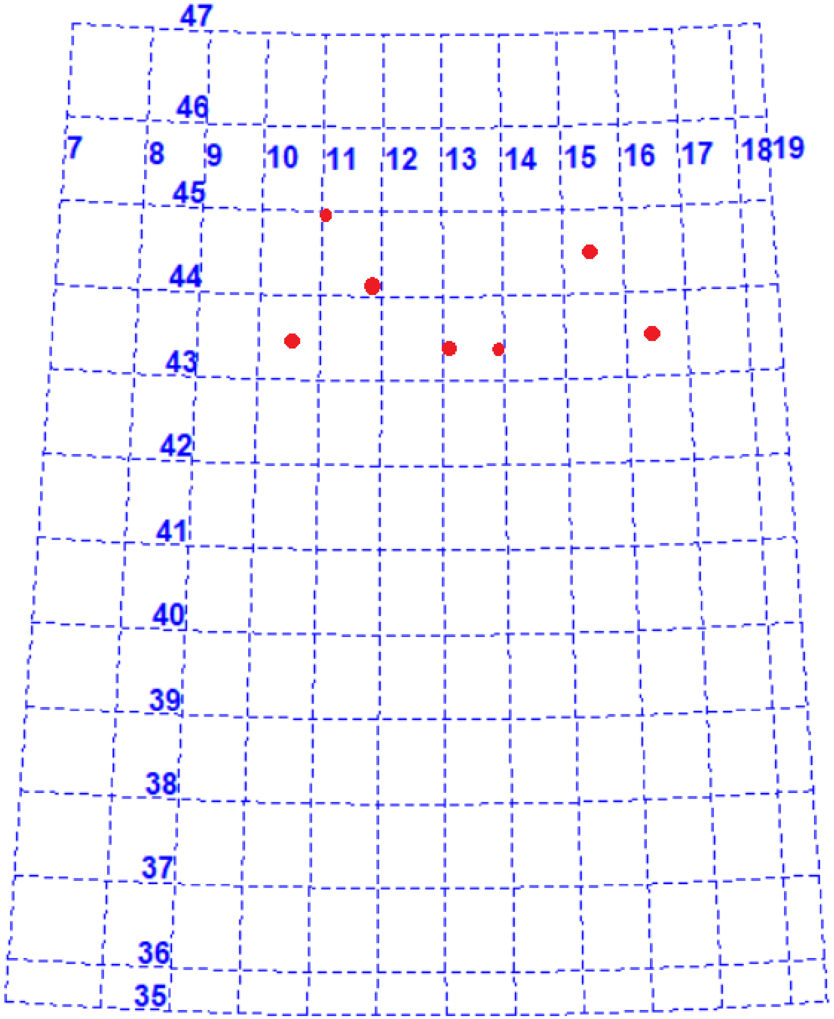
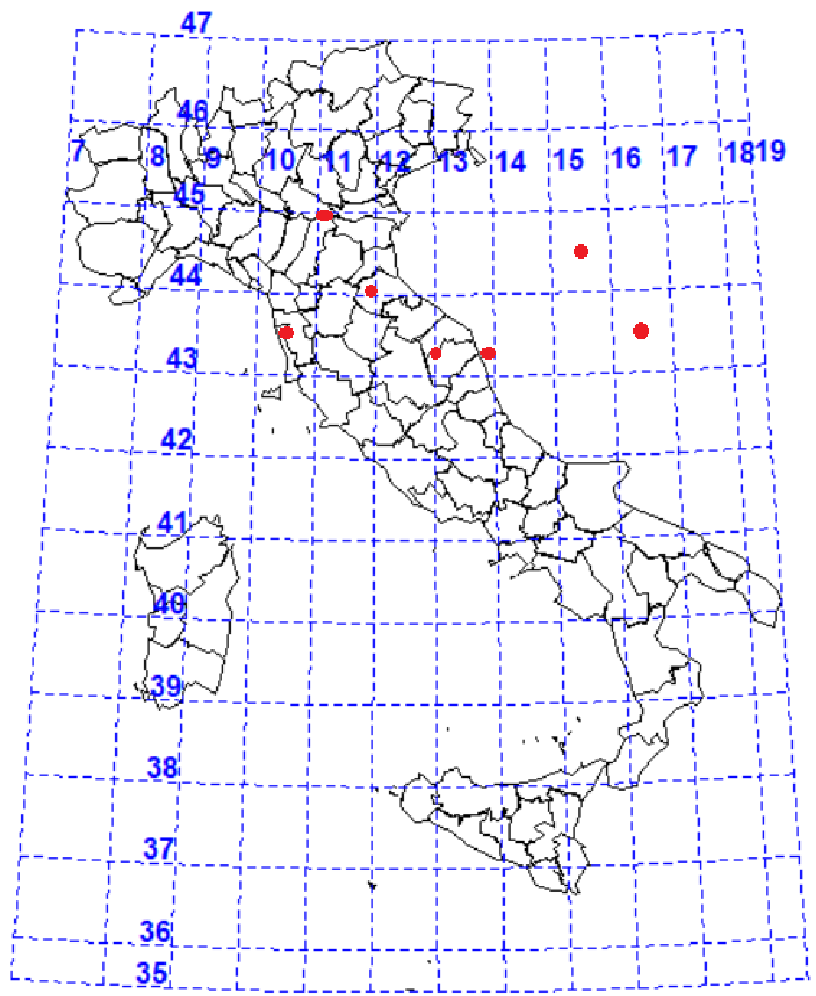
Where is that!

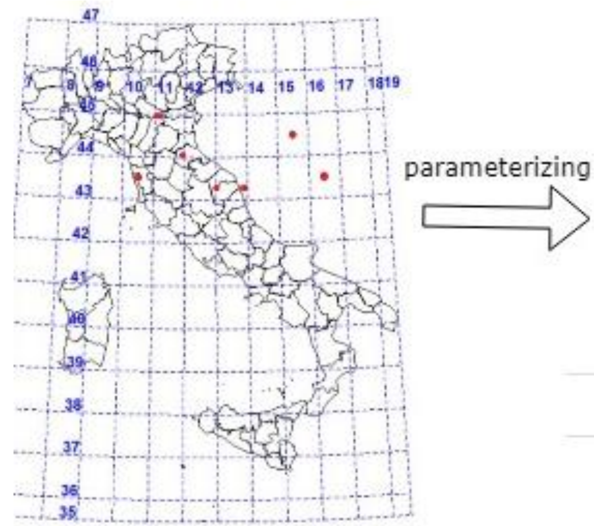


Welcome to Italy (benvenuti!) ☺



Geospatial data representation

- A spatial point is **parametrized** and represented as coordinates (longitude and latitude)
- **Geometry** inherent in the data will be **lost** by such a transformation
- Spatial reconstruction is **expensive**
  - **Spatial Join**



Longitude	Latitude
11.3709	44.5185
11.4081	44.4963
11.3477	44.499

Expensive geometry (point in polygon)

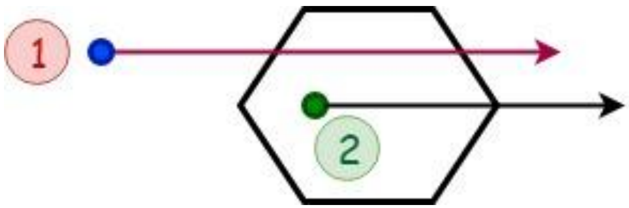
- Point-in-polygon (PIP)
  - **Ray casting algorithm**

(1) Pass a ray out from the test point

(2) Count the number of times that the ray intersects with the boundaries of the polygon

- Even → outside
- Odd → inside

easier said than done!



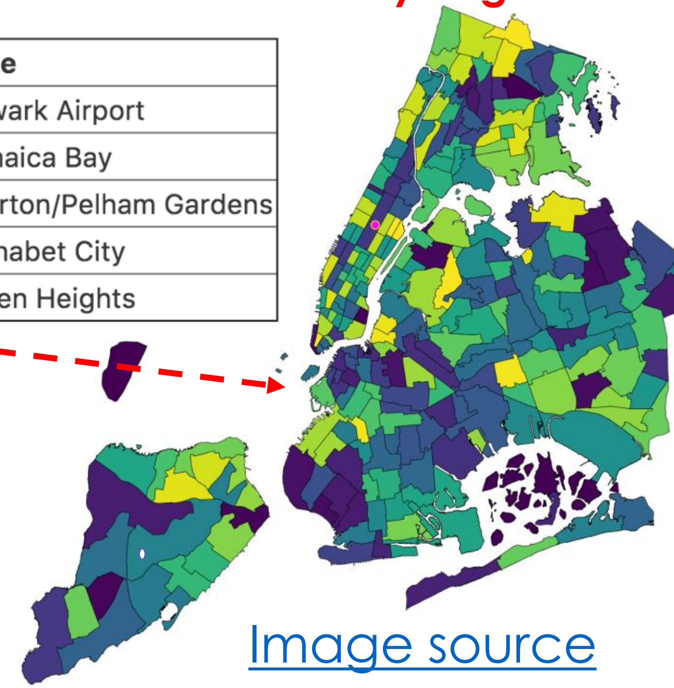
Ray casting for PIP

Spatial data analytics challenges

Shapefile, NYC

Polygons **normally huge in size**

	LocationID	borough	geometry	zone
0	1	EWR	POLYGON ((-74.18445299999996 40.6949959999999,...	Newark Airport
1	2	Queens	(POLYGON ((-73.82337597260663 40.6389870471767...	Jamaica Bay
2	3	Bronx	POLYGON ((-73.84792614099985 40.87134223399991...	Allerton/Pelham Gardens
3	4	Manhattan	POLYGON ((-73.97177410965318 40.72582128133705...	Alphabet City
4	5	Staten Island	POLYGON ((-74.17421738099989 40.56256808599987...	Arden Heights



[Image source](#)

taxi dataset

	tpep_pickup_datetime	tpep_dropoff_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude
0	2016-05-01 00:00:00	2016-05-01 00:17:31	-73.985901	40.768040	-73.983986	40.730099
1	2016-05-01 00:00:00	2016-05-01 00:07:31	-73.991577	40.744751	-73.975700	40.765469
2	2016-05-01 00:00:00	2016-05-01 00:07:01	-73.993073	40.741573	-73.980995	40.744633
3	2016-05-01 00:00:00	2016-05-01 00:19:47	-73.991943	40.684601	-74.002258	40.733002
4	2016-05-01 00:00:00	2016-05-01 00:06:39	-74.005280	40.740192	-73.997498	40.737564

Points (parametrized)
Projected Coordinate System (PCS)

assigning trips pickups to city zones (districts) is an example of a **spatial join (expensive** computationally costly workload**)**

	geometry	index_right	LocationID	borough	zone
0	POINT (-73.96599999999999 40.78)	42	43	Manhattan	Central Park

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Coping up with geo-data loads

- **Scalability**
    - Hardware scalability. **Overprovisioning** resources
    - Scaling **up/out**
- **Approximate Query Processing** (**AQP**).
    - Data **reduction**
    - **Spatial** Approximate Query Processing (**SAQP**)

Our focus!

QoS Tension

Spatial (Approximate) Query Processing (S(A)QP)

Tension

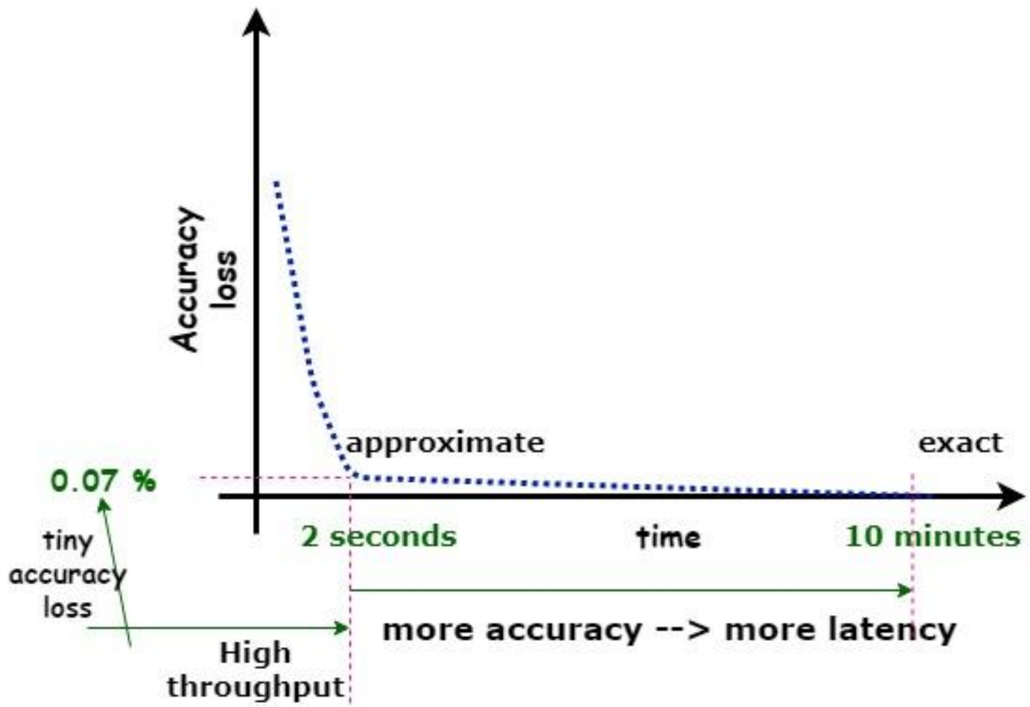
latency

Throughput

Accuracy

Spatial Approximate Query Processing

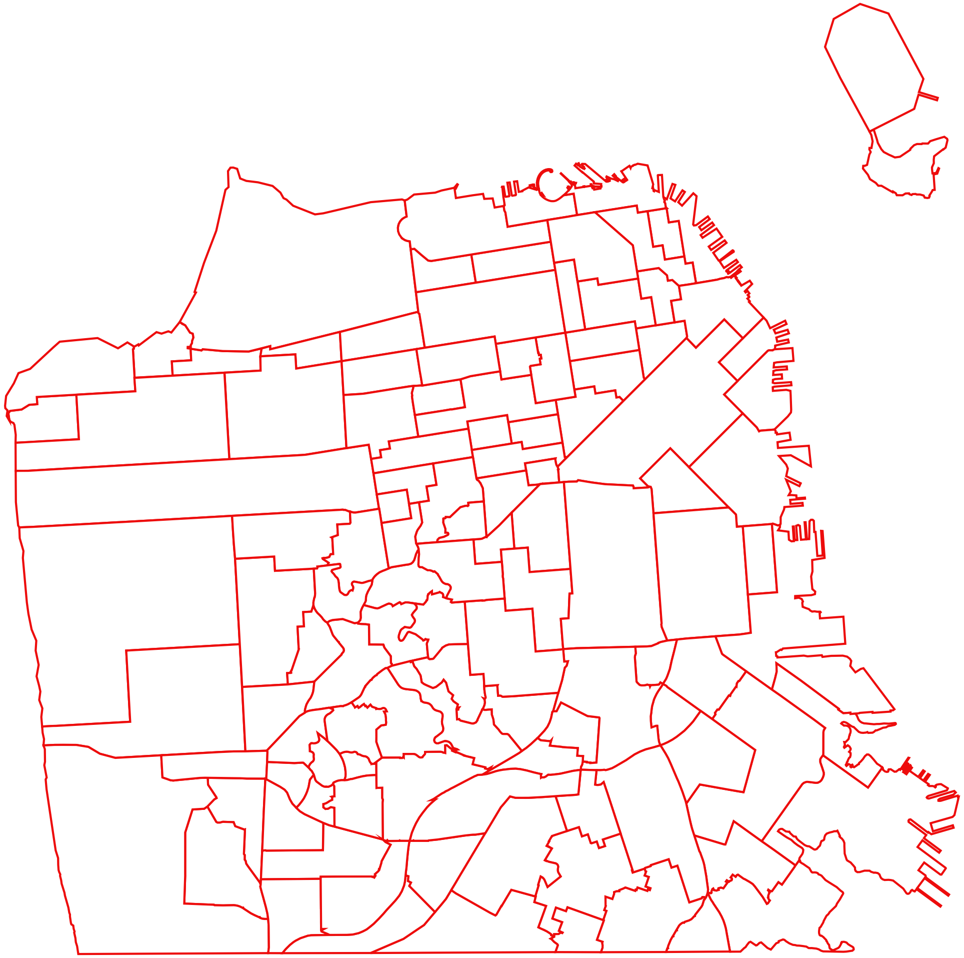
- Decision makers accept tiny **loss** in **accuracy** in exchange for a **throughput gain**



Problem

a beautiful shape of SF, USA

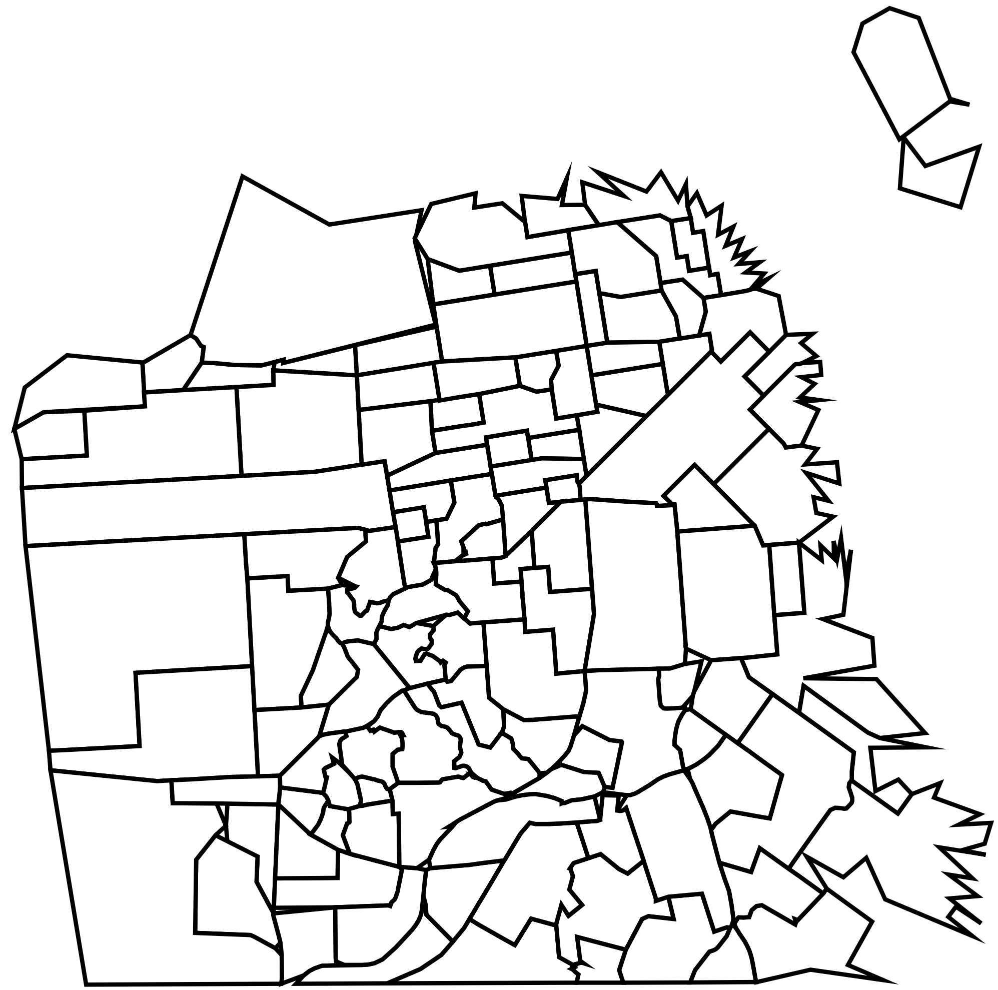
- polygon has **too many** points
- loads **slowly**
- consumes **a lot** of **memory**
  - & we don't even see the full detail



Solution

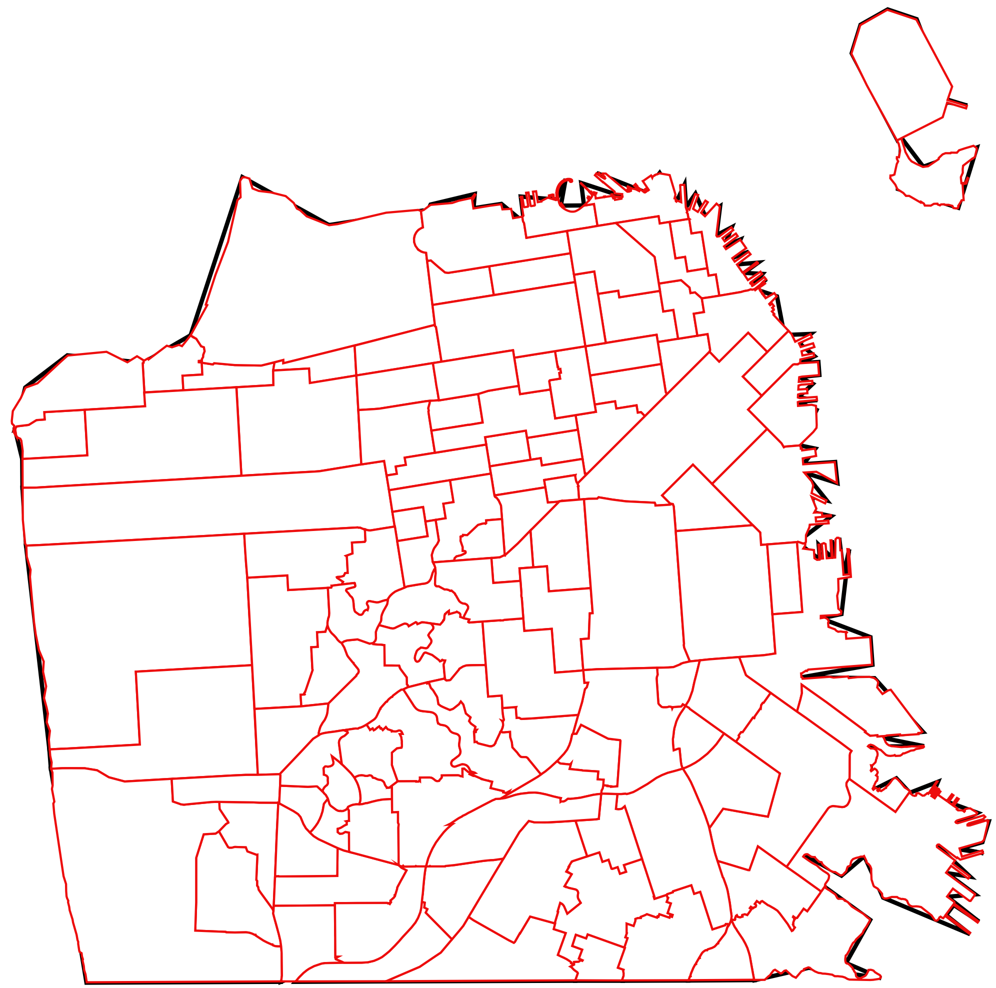
Simplify!

- express same geometry with **fewer** points
  - preserve original shape as much as possible
- Douglas-Peucker (**DP**) & Visvalingam-Whyatt (**VW**)



Difference?

- **Loads faster**
- **Memory efficient**



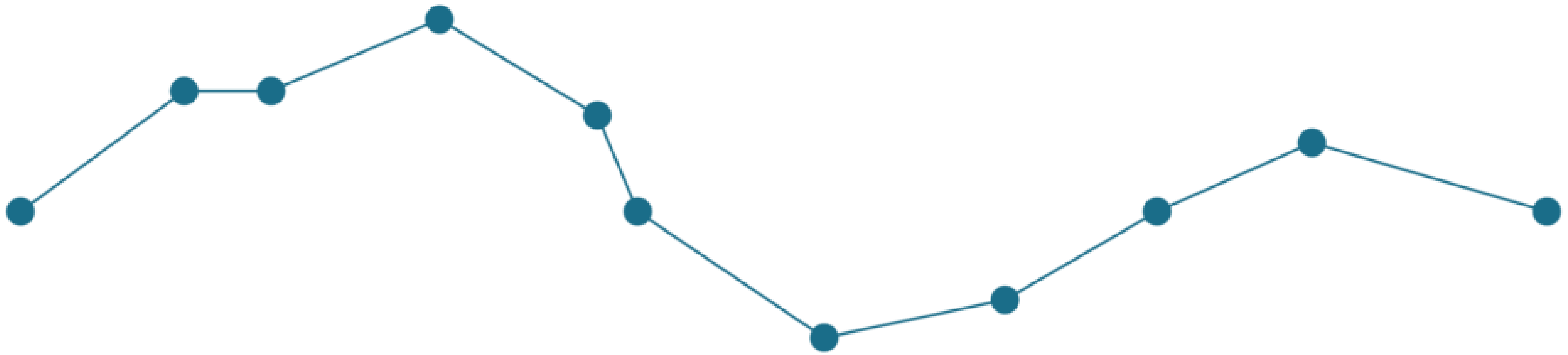
Spatial Approximate Computing

Computing over a sample instead of the whole population

Service Level Objectives:
Latency/throughput targets

Geospatial data → **sample** → SAQP → **Approximate Result** w/ rigorous Error bounds (**accuracy loss**)

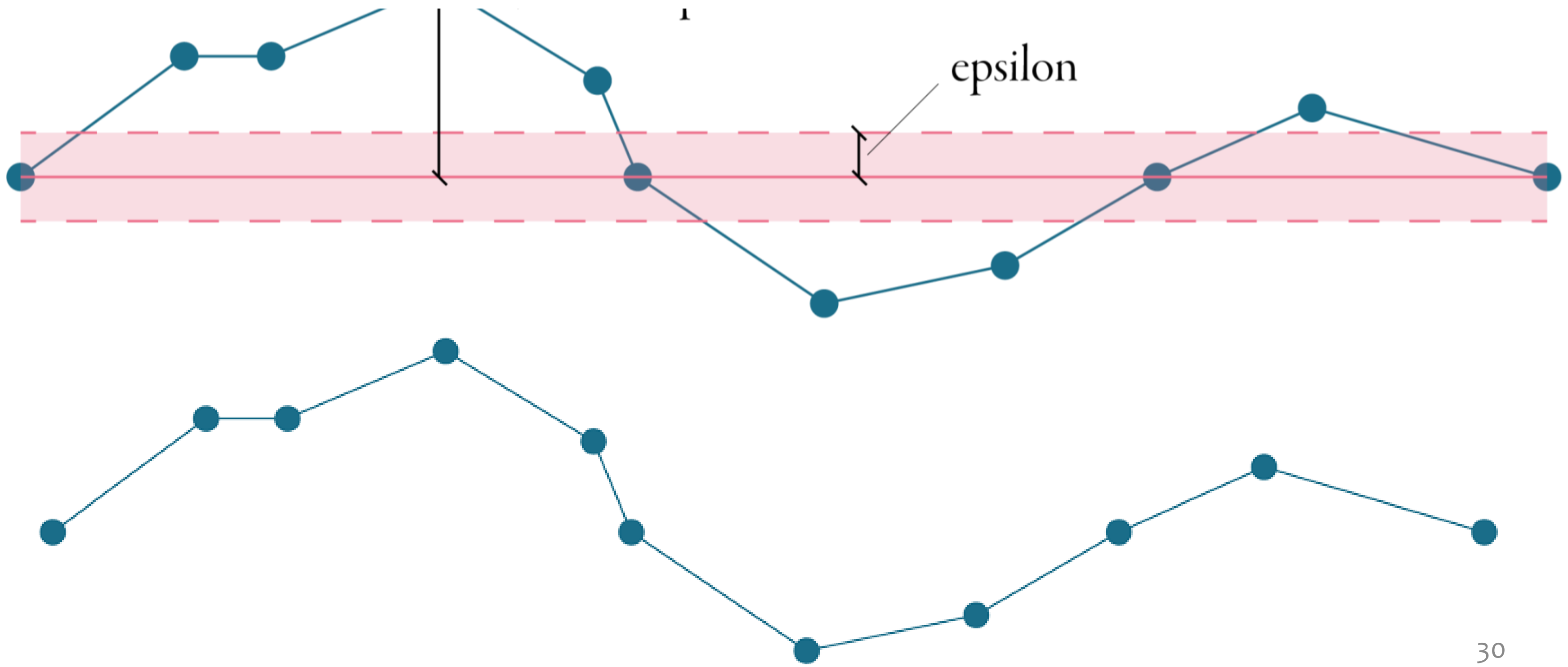
Example: Line simplification



- A **complex** line with **11** points
  - needs to be **simplified**

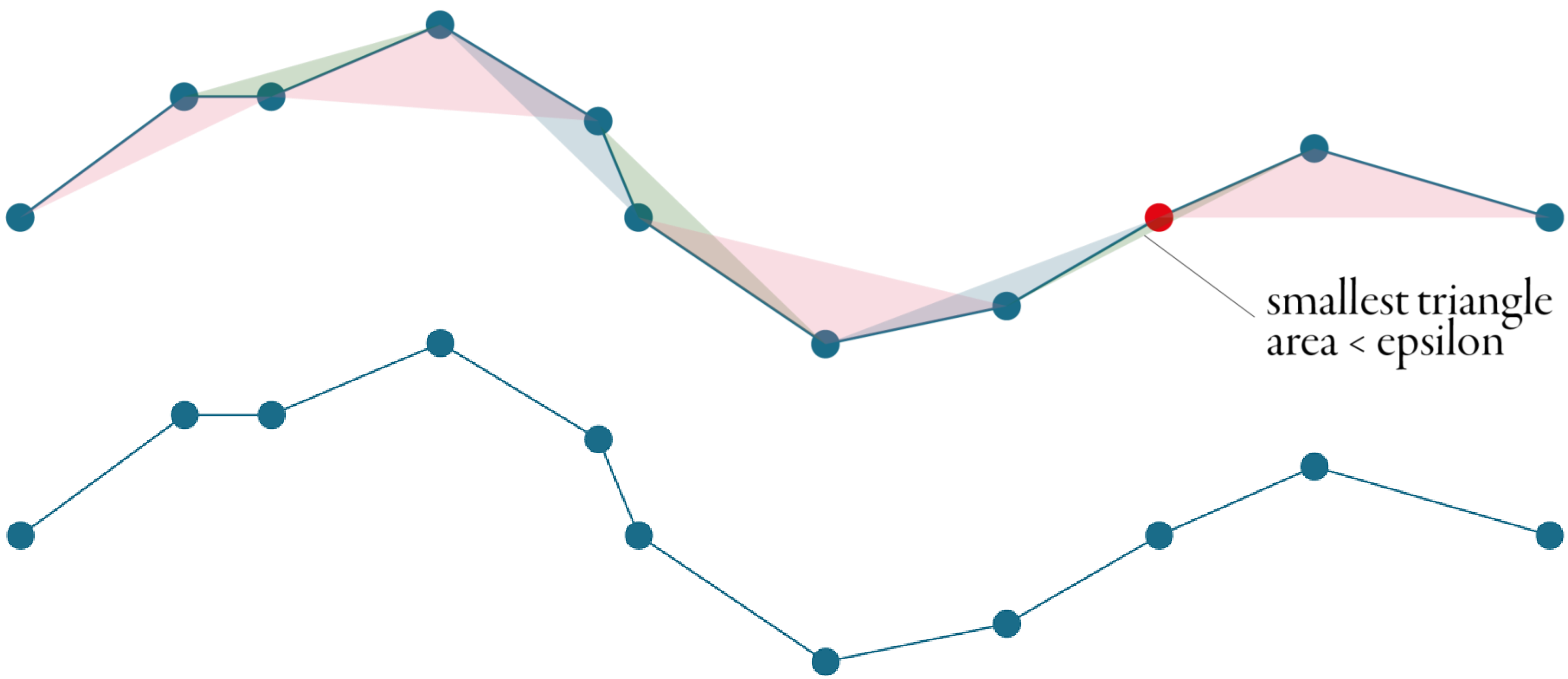
Douglas-Peucker

- remove points that are less important for overall shape
  - **No** new points
- One parameter, tolerance (*epsilon*)



Visvalingam-Whyatt

- principle is different.
  - Tolerance (epsilon) is an area, not a distance



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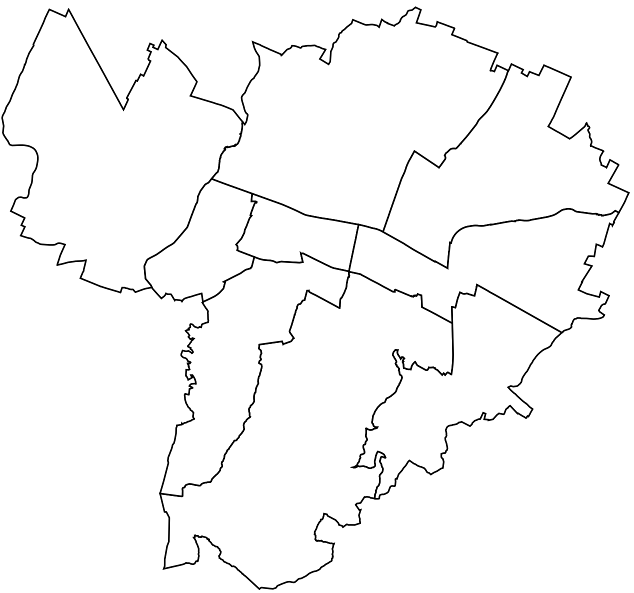
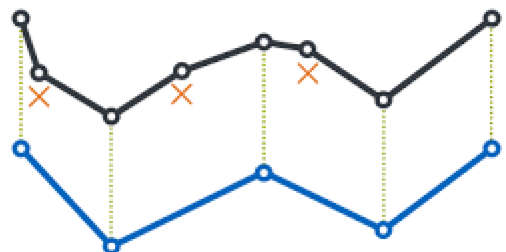
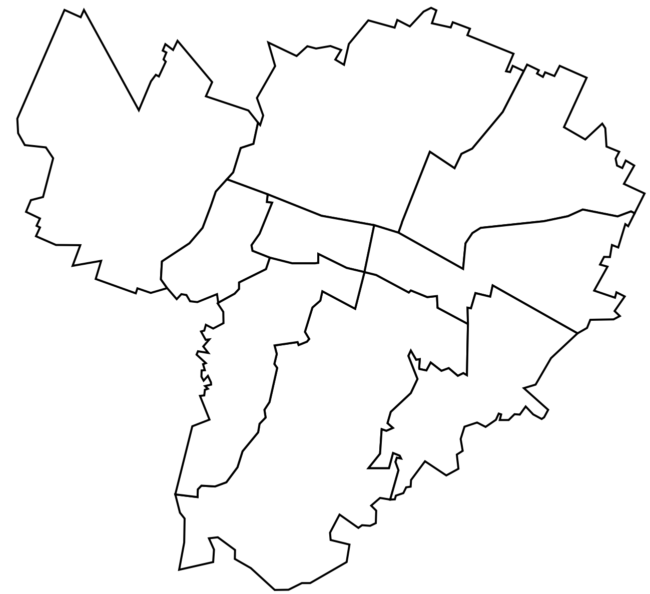
Boundary simplifier



Original polygons



Douglas-Peucker (DP)



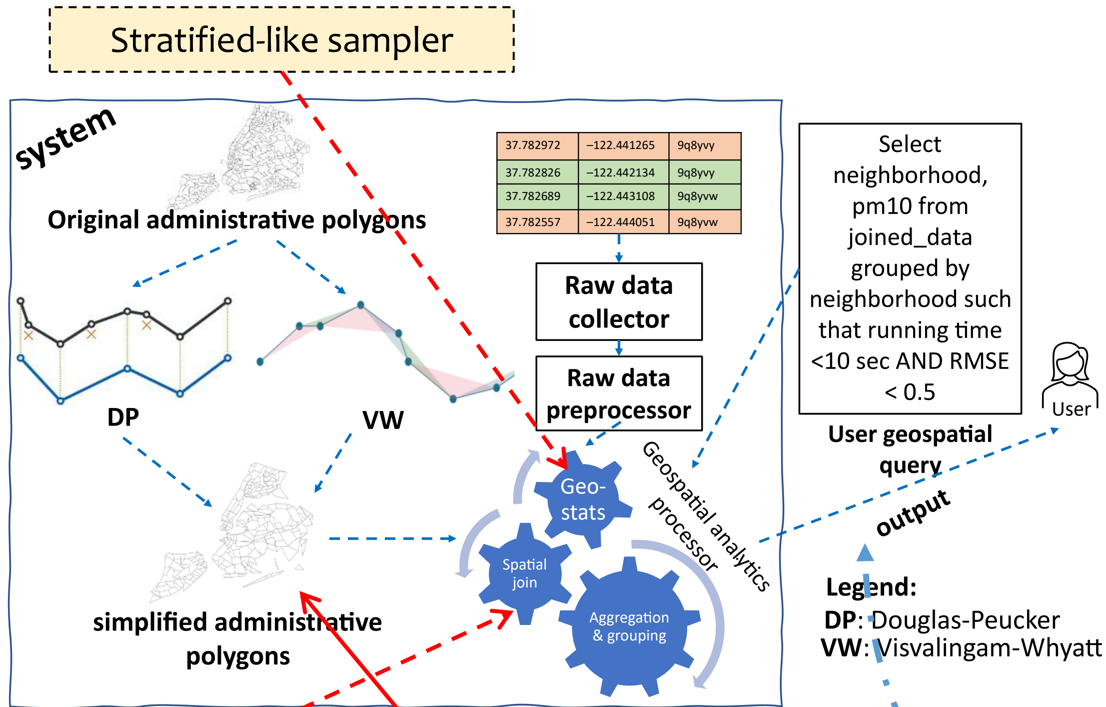
‘percentage of BPK’ 5%

Boundary **simplifier** function applied to polygons representing **Bologna** city, **Italy**

Architecture Overview: Geospatial join at Scale with QoS Guarantees

boundary **simplifier**

- DP & VW algorithms



Plain Filter-and-refine

Simplified polygons: a compact representation

Mean Absolute Percentage Error (**MAPE**), a measure of prediction accuracy, for geo-statistic group-by queries (specifically ‘mean’ queries).

$$MAPE = {}^{100\%}/_{n} \sum_{i=1}^{n} \left| {}^{AC_i - P_i}/_{AC_i} \right|$$

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Experimental setup

- **Evaluation metrics**
  - Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Spearman Correlation, and Jensen-Shannon divergence (hereafter JSD for short)
- **Baselines**
  - Plain polygon without simplification
- **Testbed**
  - We have run **experiments** on google colab
  - **Datasets**
    - polygons representing New York City neighborhoods in the USA (GeoJSON)
    - geotagged air quality dataset (NYC) collected using low-cost air-quality sensors, consisting of 170K records

See the paper for explanation!

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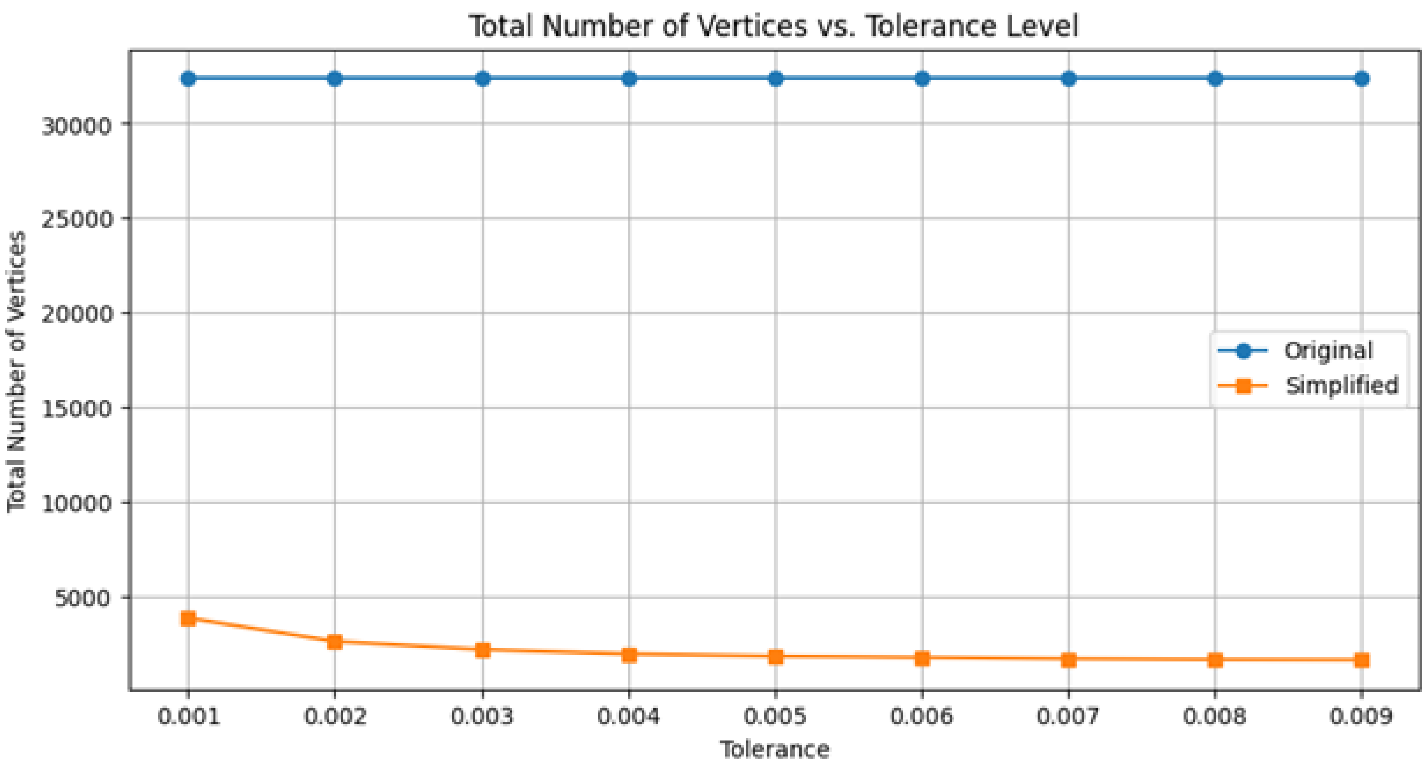
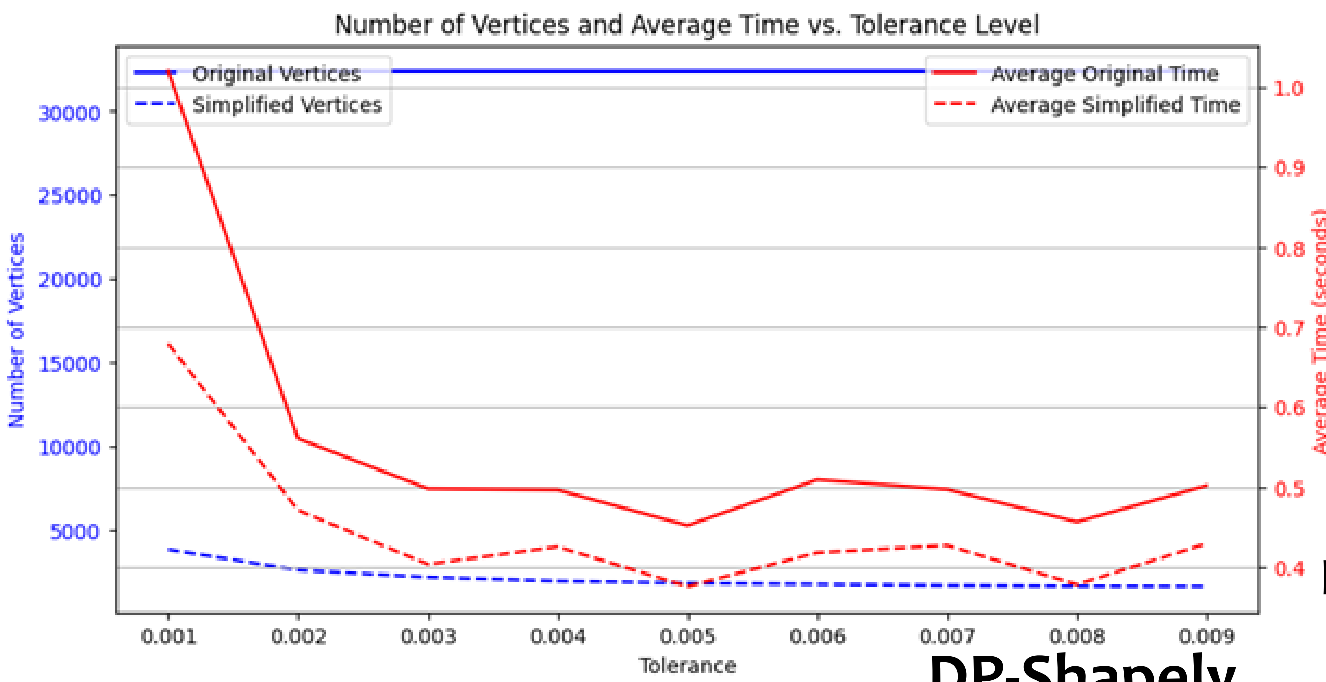
Number of Vertices vs. Tolerance, NYC polygons



Lower-better

- **Varying** the tolerance and
- **computing** total number vertices that are supplied to the system
  NYC polygons
- simplified number of vertices **decreases** with increasing tolerance, indicating a loss in detail as the number of vertices decrease

Number of Vertices vs. Tolerance vs. Average Time

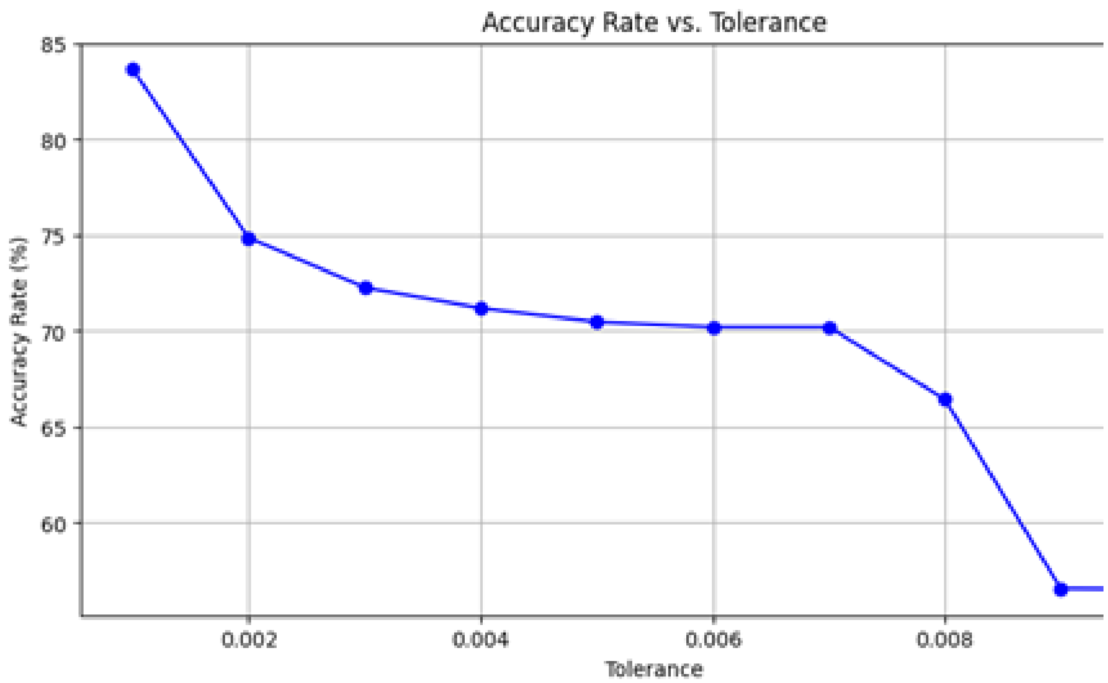


Lower-better

DP-Shapely

- **Varying** the tolerance and
- **computing** computational time required for performing the join operation (simplified Vs. baseline)
- tolerance is indirectly **proportional** to the average time of the spatial join
- as the tolerance increases, the average time and number of vertices decrease

Spatial Join Accuracy Rate vs. Tolerance



Higher
the better

- **Varying** the tolerance and
- **computing** accuracy rate
- accuracy **decreases** with increasing tolerance,
- A tradeoff between reducing complexity of data via simplification and maintaining accuracy
- significant drop in accuracy at around 0.007 tolerance
- optimal tolerance which seems to be the lowest at approximately 0.001

Spatial Join Accuracy

Metric	Algorithm	
	DP	VW
Tolerance	1%	1%
Area (m^2)	2792454.7	2260661.6
No. of Vertices	1,743	2,031
RMSE	62.69%	65.00%
MAPE	0.04758	0.04853
Spearman Correlation	0.88370	0.92074
JSD	0.33109	0.35564

- For **aggregation** workloads
- results are similar between the two algorithms (**DP** & **VW**)
    - both effective
- In terms of Spearman Correlation, **VW** performing slightly better,
    - statistically indicating that the original and simplified data are highly correlated and comparable
    - geospatial data is preserved despite reducing the number of vertices by approximately 94%

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RMSE	62.69%	65.00%
MAPE	0.04758	0.04853
Spearman Correlation	0.88370	0.92074
JSD	0.33109	0.35564

- low Jenson-Shannon Divergence (JSD)
  - similarity between original and simplified data
  - data is sufficiently well-preserved whilst decreasing computational cost.

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Concluding remarks

- **Spatial join** is indispensable
  - computationally **expensive** in full form
  - Line **simplification** is essential
  - Significantly **reducing** data size, while preserving geometric characteristics
    - cutting down computational costs, efficiency improves
- Comparing the performance of **Douglas-Peucker** & **Visvalingam-Whyatt**
  - both effective,
  - However, somehow, DP performs slightly better, but VW produces nicer-looking geometry
- **Future research,** To parallelize spatial join with simplified polygons
  - Currently, requiring original polygons files to broadcast to all cluster computing nodes

Q&A and Contacts

Thanks for your attention!

Question's time...

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