

M S A I C

A Framework for Geospatial Analytics at Scale

ORGANIZED BY  databricks

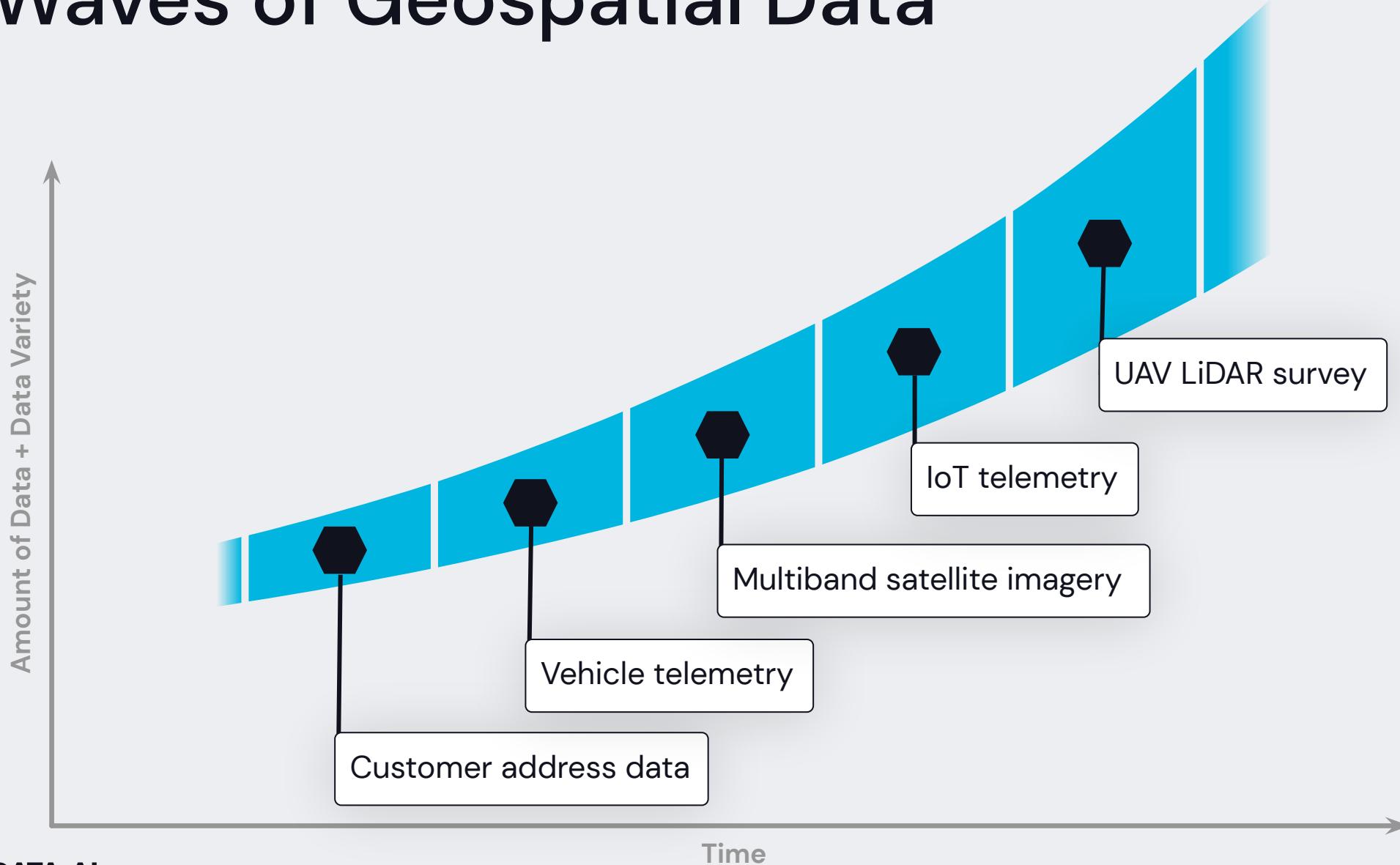


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Waves of Geospatial Data





Efficient Point in Polygon Joins via PySpark and BNG Geospatial Indexing



by [Milos Colic](#) , [Robert Whiffin](#) , [Pritesh Patel](#) , [Charis Doidge](#) ,
[Steve Kingston](#) and [Linda Sheard](#)

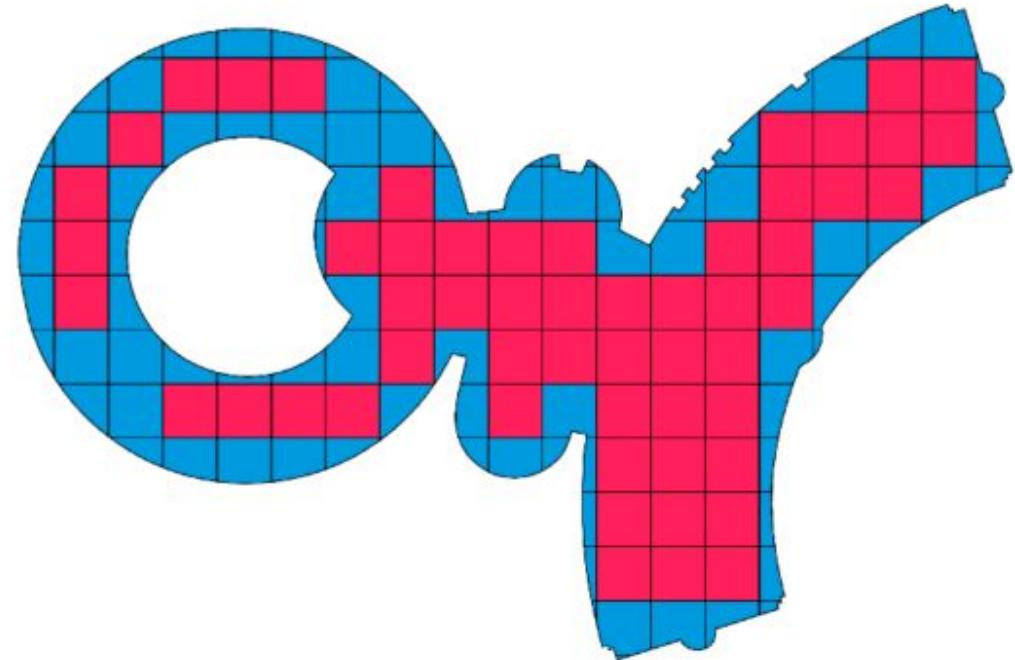
October 11, 2021 in [Engineering Blog](#)

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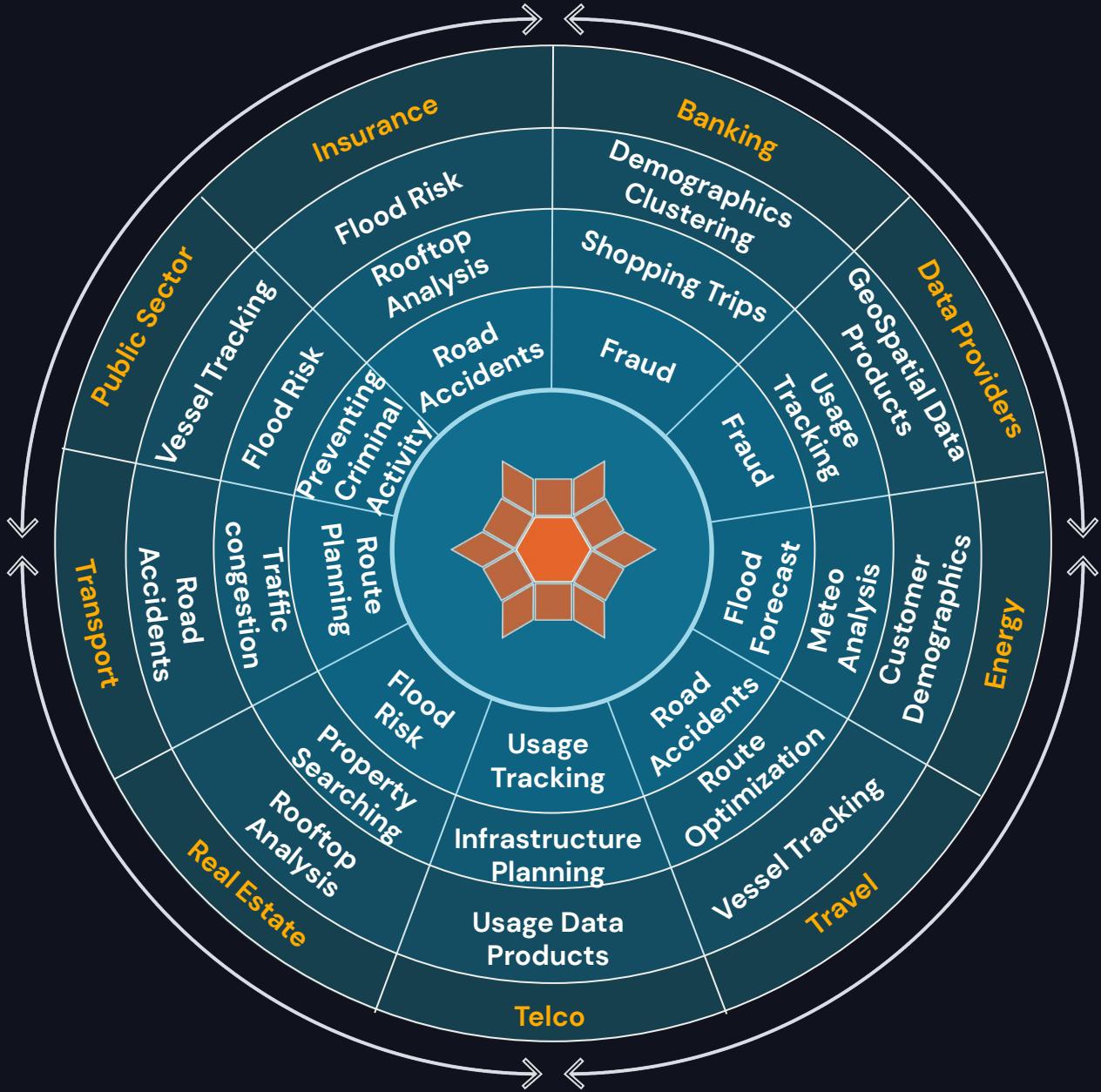
This is a collaborative post by Ordnance Survey, Microsoft and Databricks. We thank Charis Doidge, Senior Data Engineer, and Steve Kingston, Senior Data Scientist, Ordnance Survey, and Linda Sheard, Cloud Solution Architect for Advanced Analytics and AI at Microsoft, for their contributions.

This blog presents a collaboration between Ordnance Survey (OS), Databricks and Microsoft that explores spatial partitioning using the British National Grid (BNG).



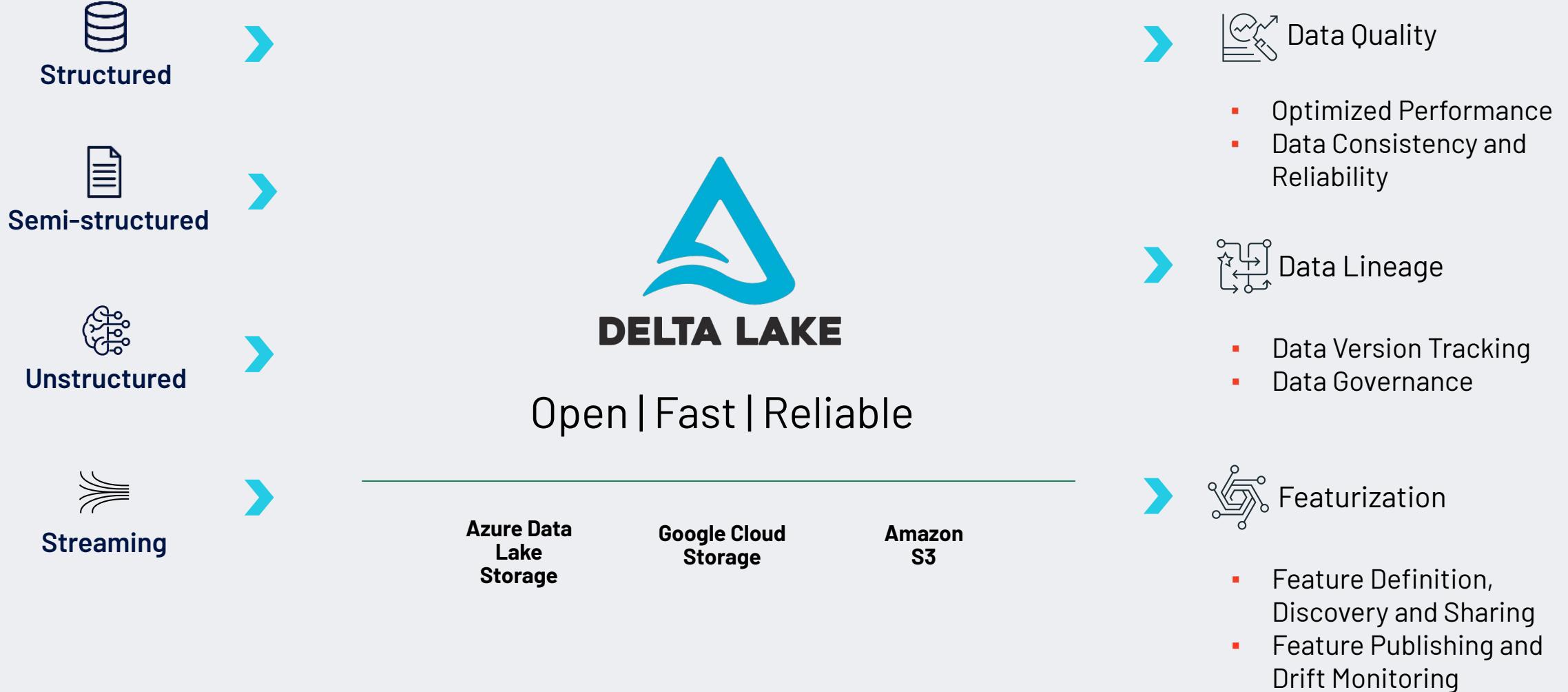
 Contained BNG indices

 Boundary BNG indices where the intersection (shared area) between polygon geometry and a given index is derived



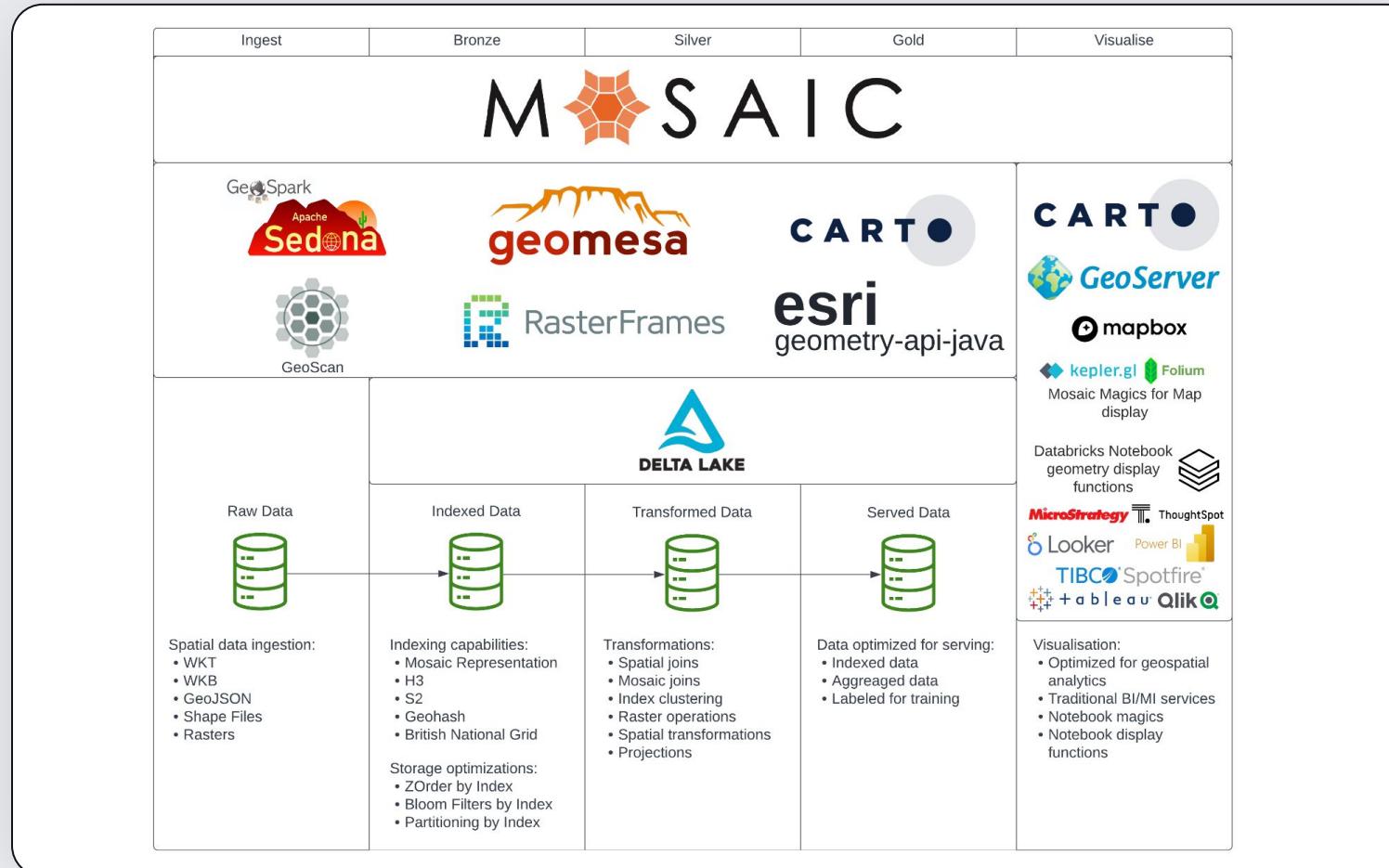
Building a data + AI driven GeoSpatial Ecosystem

Lakehouse Architecture



Mosaic Ecosystem

Easy + fast processing of very large geospatial datasets.



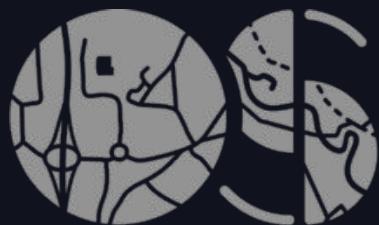
- Uniquely leverages the power of [Delta Lake](#) on Databricks
- High performance through implementation of [Apache Spark](#) Java code generation
- Flexible for use with other libraries & partners
- Unlock AI/ML + advanced analytics capabilities of geospatial data on top of Databricks Lakehouse

Uber

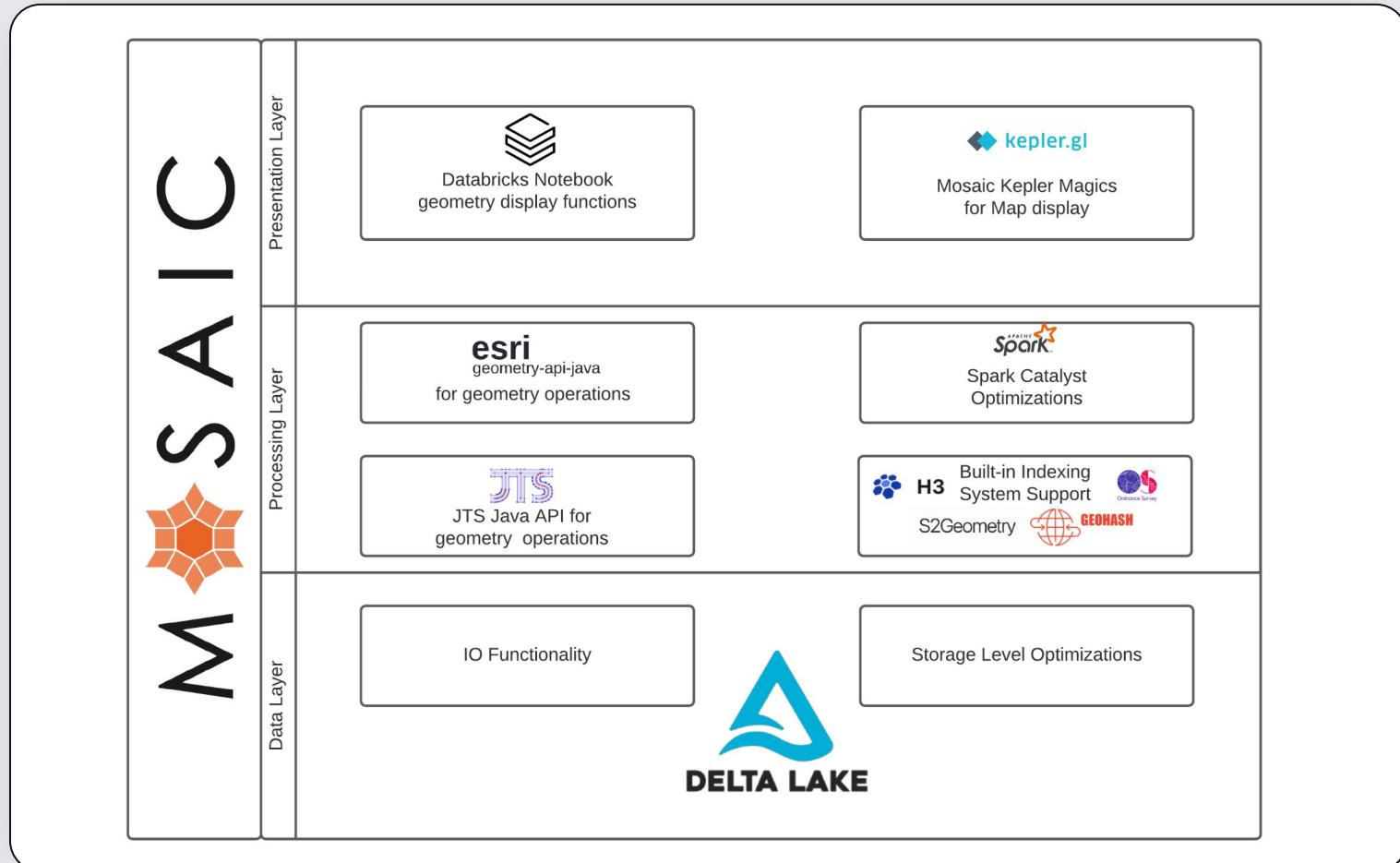
Google

esri
(geometry-api-java)

M S A I C



Design & implementation



- Spark Expressions for transforming, aggregating, indexing and joining spatial datasets
- Optimizations for performing spatial joins at scale
- Easy conversion between common spatial data encodings such as WKT, WKB and GeoJSON
- A choice of Scala, SQL, Python and R APIs
- Notebook mapping

Colocation of vessels

Unauthorized ship-to-ship transfer of goods

- Large volumes of positional data of vessels gathered from AIS transponders
- Identify if the vessels are near each other at the same point in time
- Applications in preventing criminal activity e.g. illegal exchange of goods or illegal fishing

```
21 AIS_df = (
22     spark
23     .read
24     .option("badRecordsPath", " /tmp/ais_invalid") #Quarantine
25     .csv("/tmp/vessels/2018", header=True, schema=schema)
26     .filter("VesselType = 70") # Only select cargos
27     .filter("Status IS NOT NULL")
28 )
29 display(AIS_df)
```

Table Data Profile

	MMSI	BaseDateTime	LAT	LON	SOG	COG	Heading	VesselName	IMO
1	265491000	2018-01-01T00:00:06.000+0000	39.02249	-76.37648	15.4	162.3	162	MIGNON	IMO9189251
2	316029000	2018-01-01T00:00:00.000+0000	44.71361	-82.79381	11.9	161.4	161	CSL NIAGARA	IMO7128423
3	316001797	2018-01-01T00:00:03.000+0000	43.65205	-82.29167	4.5	-50.6	345	ALGOWAY	IMO7221251
4	370024000	2018-01-01T00:00:01.000+0000	46.19988	-123.42848	13.7	9.4	9	SANTA VISTA	IMO9527946
5	636091883	2018-01-01T00:00:00.000+0000	33.80496	-78.04026	15.2	194.4	195	ZIM COLOMBO	IMO9456977
6	311000310	2018-01-01T00:00:03.000+0000	23.18602	-79.91904	13	110.5	110	BTG EVEREST	IMO9687837

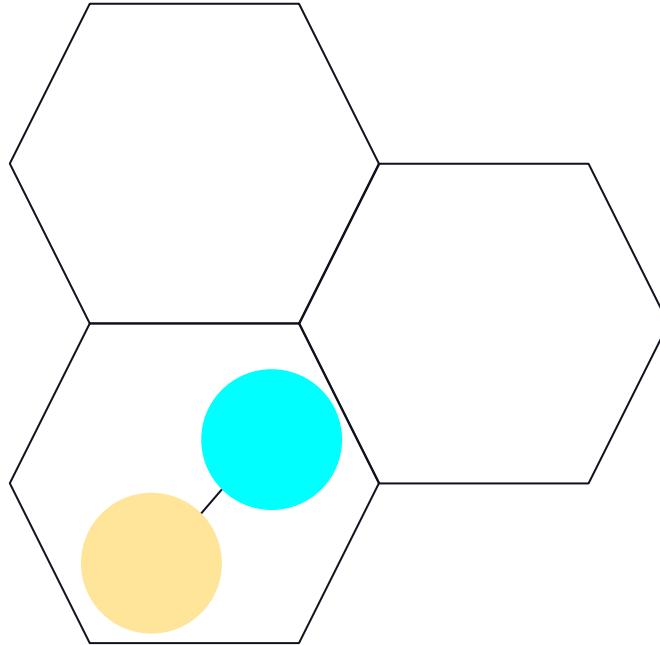
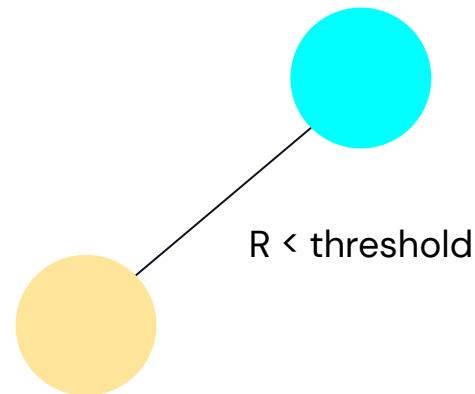
Colocation of vessels

Unauthorized ship-to-ship transfer of goods



Naive approach

Distance Join



- Cross product of all position pairs that occur at the same time
- Very costly
- Skewed on time axis can cause query never to finish
- Use index system (e.g. H3) to avoid endless compute

Naive approach

Long running job that ultimately fails

Cmd 15

```
1 | (c
2 |   cargos_indexed.alias("left")
3 |   .crossJoin(cargos_indexed.alias("right"))
4 |   .where(st_distance(col("left.point_geom"), col("right.point_geom")) < buffer)
5 |   .where((col("left.timestamp").cast("long") - col("right.timestamp").cast("long")) > 600)
6 | ).count()
```

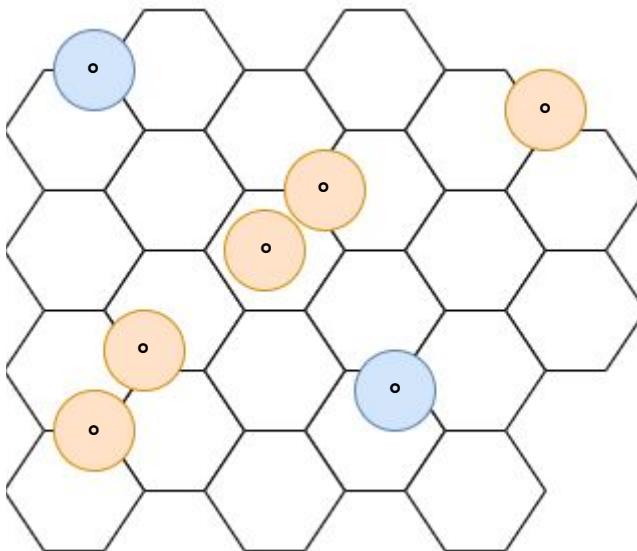
▶ (1) Spark Jobs

⊕org.apache.spark.SparkException: Job aborted due to stage failure: Task 0 in stage 17.0 failed 4 times
1): ExecutorLostFailure (executor 1 exited caused by one of the running tasks) Reason: worker lost

Command took 11.42 hours -- by milos.colic@databricks.com at 27/06/2022, 14:46:32 on MosaicDemo

Buffer approach

Mosaic Polygon Intersection Join



- Represent points as circles by buffering
- Index using Mosaic
- Run polygon intersection join using Mosaic

Buffer approach

Install & enable Mosaic

```
Cmd 2
1 %pip install databricks-mosaic
Python ▶▼ ▾ - ✎
```

```
Cmd 3
1 from pyspark.sql.functions import *
2 from mosaic import *
3 enable_mosaic(spark, dbutils)
Python ▶▼ ▾ - ✎
```

Command took 1.33 seconds -- by stuart.lynn@databricks.com at 27/06/2022, 14:40:31 on
Shared Autoscaling EMEA

Buffer approach

Buffer positions

Cmd 6

```
1 one_metre = (0.00001 -      0.000001)
2 buffer = 100 * one_metre
3
4 (
5   cargos_indexed
6   .withColumn('buffer_geom', st_buffer("point_geom", lit(buffer)))
7   .withColumn("ix", mosaic_explode("buffer_geom", lit(9)))
8   .write
9   .mode('overwrite')
10  .saveAsTable('ship2ship.cargos_buffered')
11 )
```

▶ (4) Spark Jobs

Command took 14.98 minutes -- by milos.colic@databricks.com at 15/06/2022, 07:21:41 on MosaicDemo

Buffer approach

Index vessel data and z-order

Cmd 7

We can optimise our table to colocate data and make querying faster

```
1 %sql
2 OPTIMIZE ship2ship.cargos_buffered ZORDER BY (ix.index_id, timestamp);
3 SELECT * FROM ship2ship.cargos_buffered;
```

▶ (13) Spark Jobs

Table Data Profile

	latitude	longitude	sog	heading	status	point_geom	ix
1	40.68374	-74.07344	0	132	5	AQEAAAD4ja89s4RSwMh71cqEV0RA	▶ {"is_core": false, "index_id": "617733150546591743", "wkb": "AQMAAAABAAAAYQAAAPiNrz2zhFLASDMWTWdXREA6FsxGsoF (truncated)"}
2	49.30762	-123.1868	0.1	244	1	AQEAAAkufyH9MtewDrMlxgdp0hA	▶ {"is_core": false, "index_id": "617712098091991039", "wkb": "AQMAAAABAAAAGwAAACS5/lf0v17AuoPYmUKnSEBmQRmR88t"}

Truncated results, showing first 1000 rows.
Click to re-execute with maximum result limits.

grid

Command took 23.04 seconds -- by milos.colic@databricks.com at 15/06/2022, 07:37:20 on MosaicDemo

Buffer approach

Join on index and only perform intersection if necessary

```
candidates = (
    buffered_events.alias("a")
    .join(
        buffered_events.alias("b"),
        [col("a.ix.index_id") == col("b.ix.index_id"), ←
         col('a.mmsi') < col('b.mmsi'), ←
         ts_diff('a.timestamp', 'b.timestamp') <
            time_window("a.sog_kmph", "b.sog_kmph", "a.heading", "b.heading", buffer)
        ]
    )
    .where(
        (col('a.ix.is_core') | col('b.ix.is_core')) ←
        | st_intersects('a.ix.wkb', 'b.ix.wkb') ←
    )
)
```

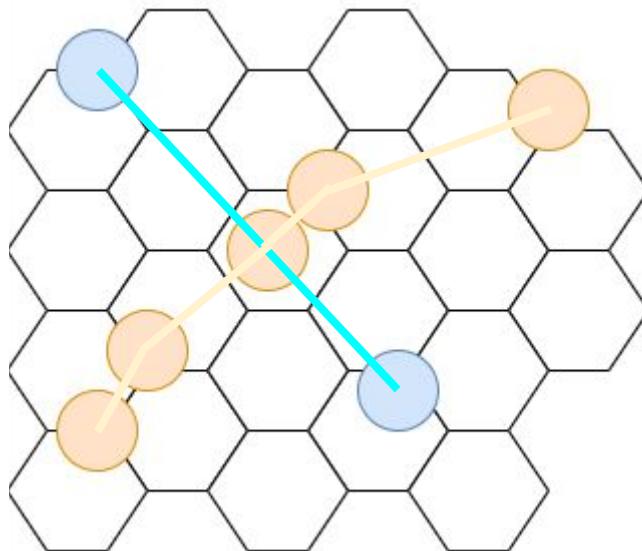
to only compare across efficient indices
to prevent comparing candidates bidirectionally

if either candidate fully covers an index, no further comparison is needed
limit geospatial querying to cases where indices are not enough

Command took 31.35 minutes -- by milos.colic@databricks.com at 15/06/2022, 09:31:26 on MosaicDemo

Line String approach

Mosaic Polygon Intersection Join

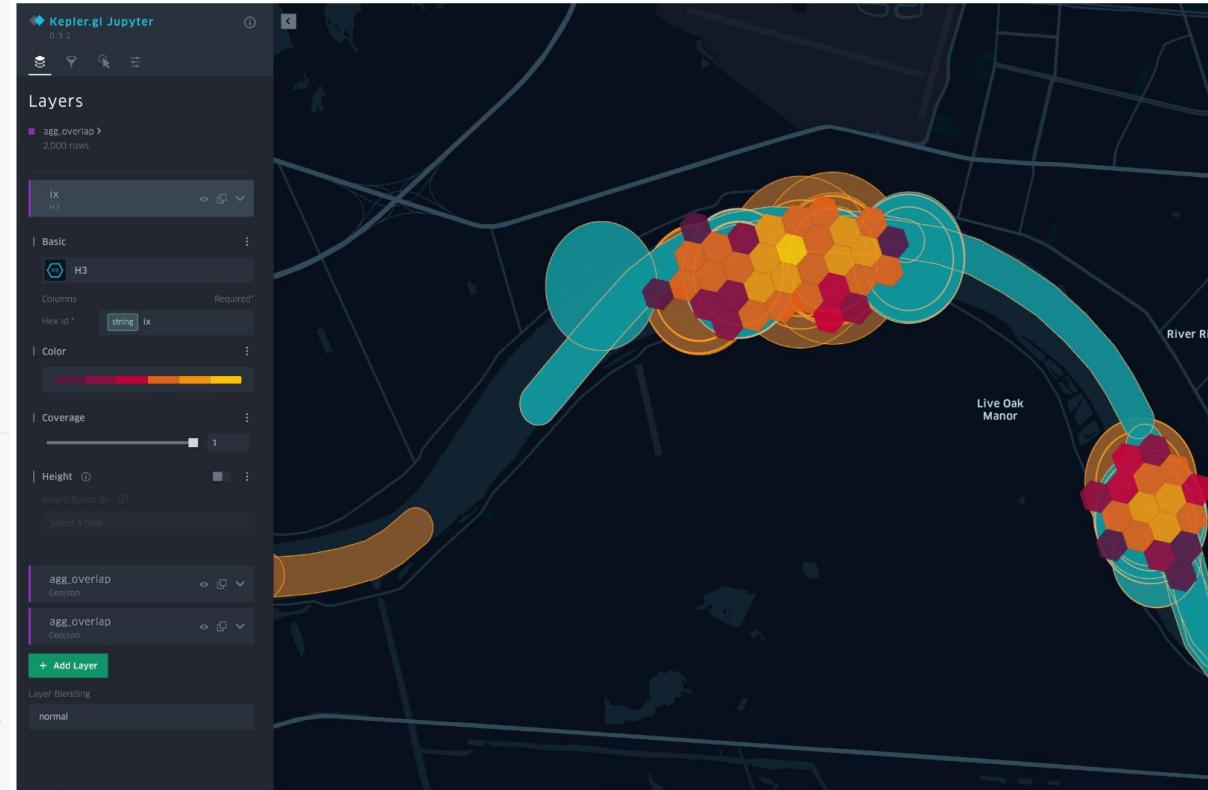


- Connect the points into lines and buffer
- Index line polygons using Mosaic
- Run polygon intersection join using Mosaic

Line String approach

Mosaic Polygon Intersection Join

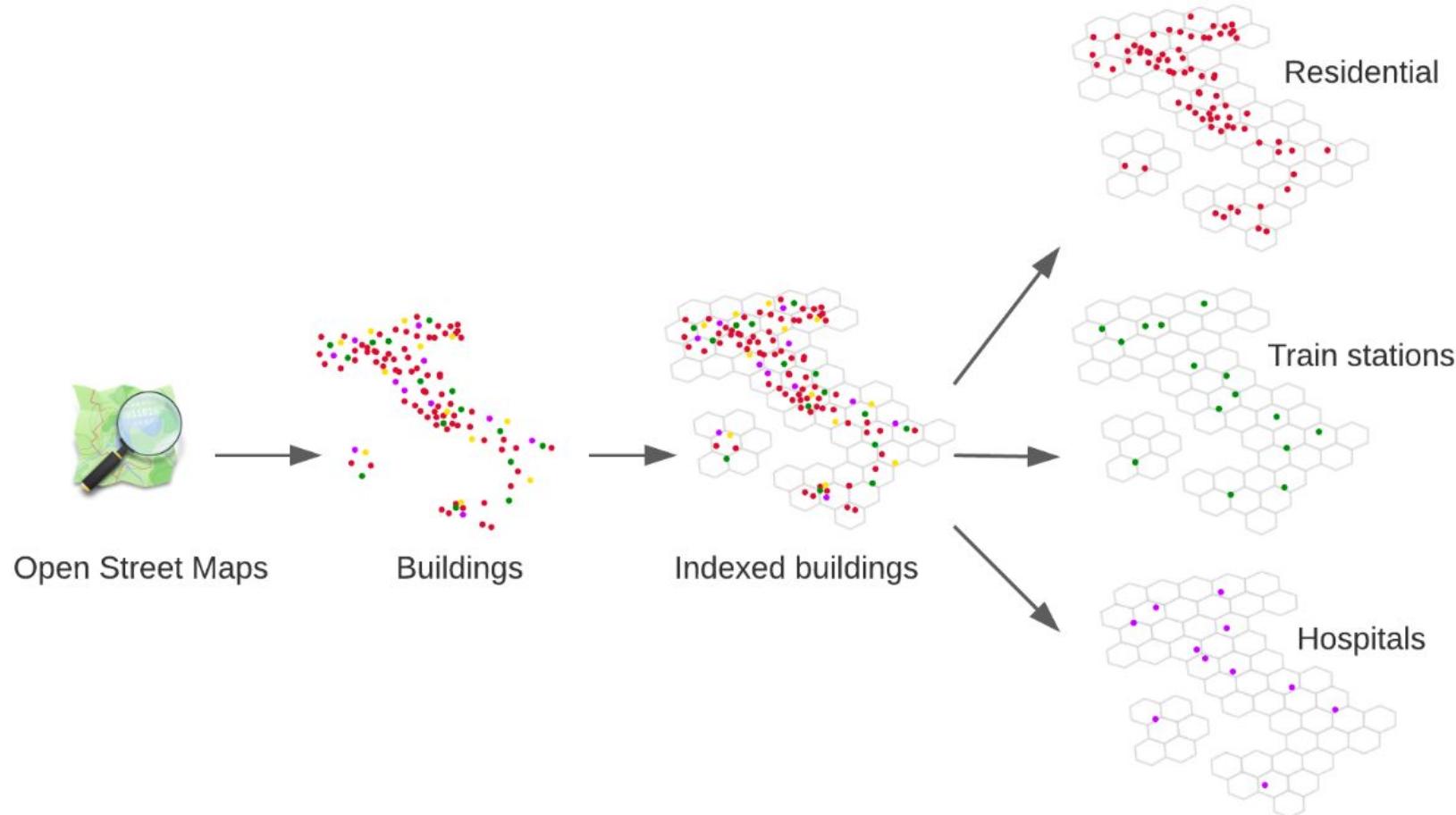
```
1 lines = (cargos_indexed
2   .repartition(sc.defaultParallelism * 20)
3   .groupBy("mmsi", window("timestamp", "15 minutes"))
4   .agg(
5     collect_list(struct(col("point_geom"), col("timestamp")))
6     .alias("coords")
7   )
8   .withColumn("coords", expr("""
9     array_sort(coords, (left, right) =>
10       case
11         when left.timestamp < right.timestamp then -1
12         when left.timestamp > right.timestamp then 1
13         else 0
14       end
15     )"""))
16   .withColumn("line", st_makeline(col("coords.point_geom")))
17   .cache()
18 )
19
20 one_metre = (0.00001 - 0.000001)
21 buffer = 200 * one_metre
22
23 def get_buffer(line):
24   np = expr(f"st_numpoints({line})")
25   max_np = lines.select(max(np)).collect()[0][0]
26   return lit(max_np) * lit(buffer) / np # inverse proportional to
27   # number of points, larger buffer for slower ships
28
29 cargo_movement = (
30   lines
31   .withColumn("buffer_r", get_buffer("line"))
32   .withColumn("buffer_geom", st_buffer('line', col("buffer_r")))
33   .withColumn('buffer', st_astext('buffer_geom'))
34   .withColumn('ix', mosaic_explode('buffer_geom', lit(9)))
35 )
```



Command took 6.88 minutes -- by milos.colic@databricks.com at 28/06/2022, 02:46:08 on MosaicDemo

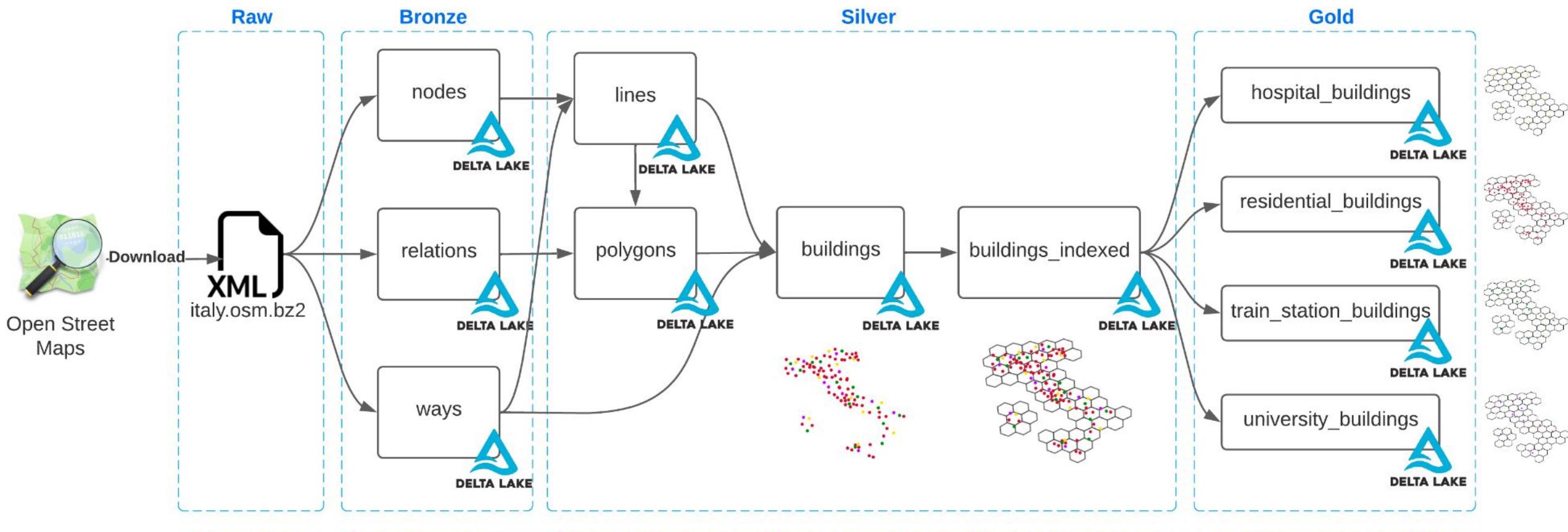
Processing OpenStreetMap data with Live Tables

Creating feature layers from OSM



Processing OpenStreetMap data with Live Tables

Creating feature layers from OSM



Purpose-built for Geospatial Analytics



Solutions

Purpose built solution accelerators that address the highest value use-cases in many industry verticals.



Solution Partners

Experienced partners help accelerate solutions with Lakehouse in geospatial analytics domain.



Data Sharing & Ecosystem

Consume geospatial data from any data vendors and monetize insights through Delta sharing.



Connectors & Data Models

Connectors to common data sources and solutions for common data models.



Databricks Product Aligned

Geospatial functionality coming to Databricks product natively and powered by Photon.



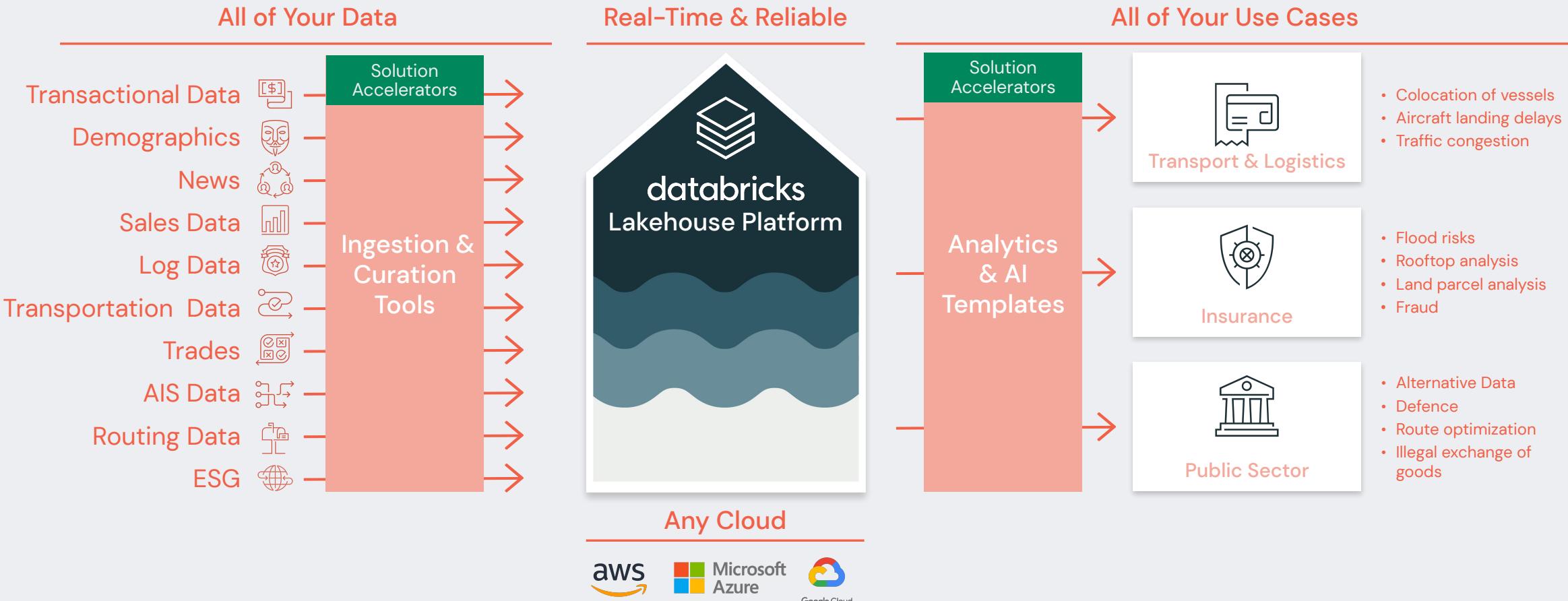
Industry Collaboration

Integrated Lakehouse into multiple geospatial OSS projects in the market today.



Geospatial Analytics on Lakehouse

Helping organizations build a data asset strategy to enable multiple use cases



Thank you



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Stuart Lynn

Sr. Solutions Architect,
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MOSAIC
■ [Documentation](#)
■ [Github Repo](#)