# Next-gen Analytics Innovation for Connected Vehicles & Telemetry Data

 $(OCIENT)^{\scriptscriptstyle{TM}} \rightarrow$ 



# **DYLAN MURPHY**

### **Director of Product at Ocient**

- 20 Years of Enterprise Analytics Experience
- IBM, Startup CEO, Mentor
- Jiu Jitsu Competitor, Dad, House Renovator

### VEHICLE TELEMATICS AT HYPERSCALE

Why is hyperscale needed for telematic data?

# By 2025, there will be 116 million connected cars in the U.S.

 and according to one estimate by Hitachi, each of those connected cars will upload <u>25 gigabytes</u> of data to the cloud per hour.

If you do the math, that's **219 terabytes** each year, and by 2025, it works out to roughly **25 billion terabytes** of total connected car data each year.

- Vehicle telematics capture & communicate diagnostic datapoints at set intervals
- Datapoints typically include GPS based locations and timestamps
- Battery levels and other IoT data is captured for electric vehicles (EVs)
- Telematics for a fleet of 1000s of vehicles at one second intervals over several years can result in **trillions** of datapoints

# KEYS TO GEOSPATIAL EXCELLENCE

What is required to analyze this type of geospatial data?

### **Broad Support of Geospatial Functionality**

• A complete GIS Stack suited for large scale geospatial analytics

### **Performance at Hyperscale**

• GIS functions that operate across **Trillions** of datapoints in **seconds** 

### **High-performance Ingest and Adjacent Analytics**

Leverage the power of geospatial analytics from loading to presentation

# INTRODUCING OCIENT

A hyperscale data analytics solutions company, enabling organizations to accelerate data-driven business transformation with the lowest operational cost

- ✓ Powered by a high-performance data warehouse platform that scales without limits
- Native support for geospatial datatypes, geospatial indexes, and third-party integrations
- ✓ In-database Machine Learning coupled with Geospatial for Advanced Analytics

#### **Trip Details**

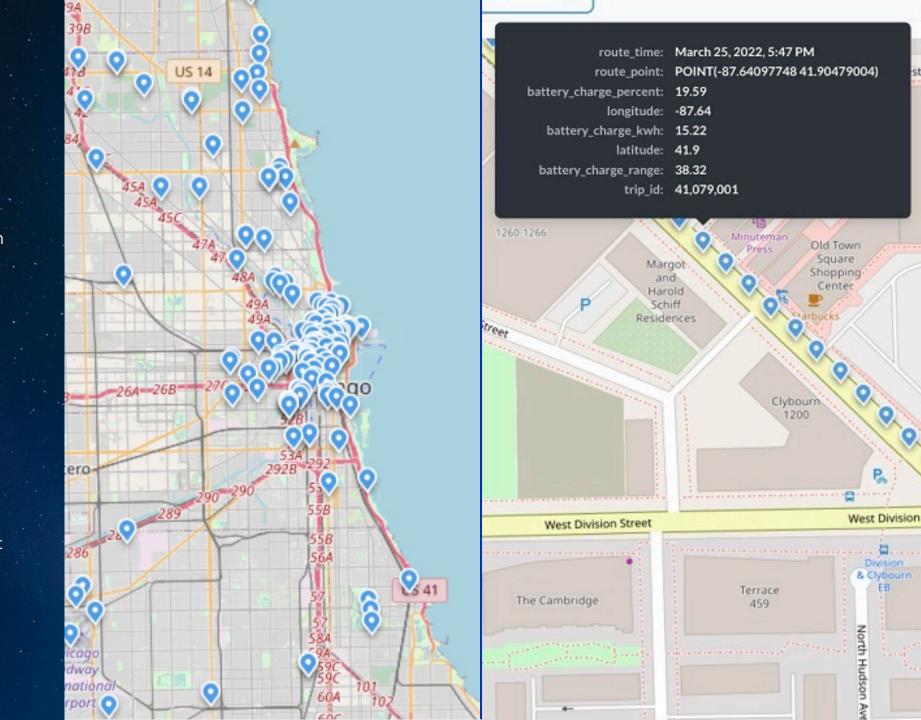
- 150 Million Trips
- ¼ Trillion Trip Points (250 Billion Telemetric Data Points)
- Second-by-second details on location, battery level, battery range, etc.

#### **Charging Stations**

- Locations throughout Chicago
- Vehicle charging events for each station

#### **Taxi Details**

Types and details of the different taxis taking trips



# TOOLS TO IDENTIFY "CHARGING DESERTS"

Areas where vehicles tend to require a charge, but no local charging stations exist

#### **Extremely Fast Access to Underlying Data**

#### **Time Partitioning**

Isolate the relevant data by time from 250+ Billion records

#### **Secondary Indexing**

Isolate the relevant data by battery charge range from the set of time-partitioned data above

### **Extremely Fast Geospatial Analysis**

#### **Distance Calculations**

Determine the distance between billions of trip points and the charging stations

#### **Clustering Geographic Data**

Determine clusters of points that represent areas for potential new charging stations

#### **Creating Geospatial Objects**

- Create lines from drop-off locations
- Return a circular polygon of the identified clustered locations for new stations

## **IDENTIFYING CHARGING DESERTS**

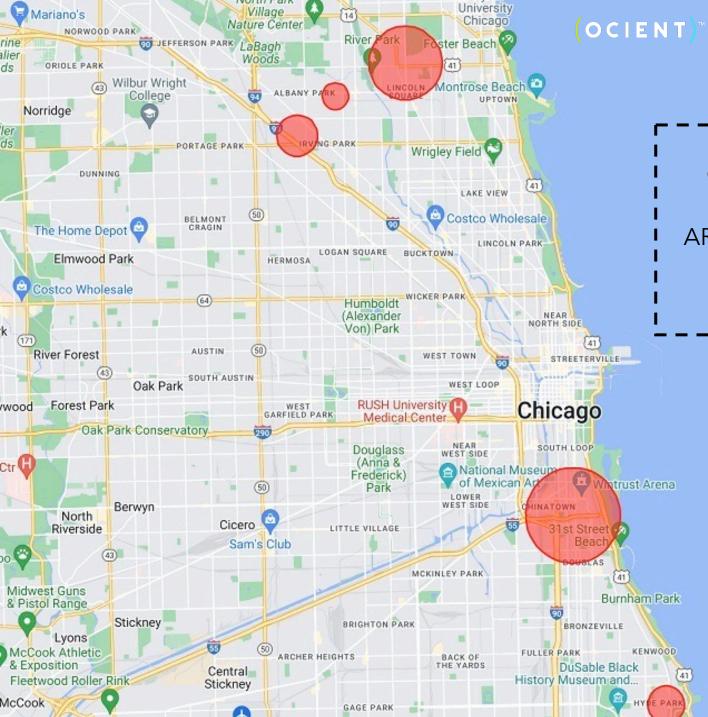
### A Single powerful Query leveraging Hyperscale, GIS, and Analytics

Select low battery levels from 100s of Billions of telemetric data points in seconds, enabled by CASA and hyperscale indexes

Use geospatial analytics functions to find the points furthest from available charging stations

Use geospatial analytics functions to identify clusters of points and group them into geographic areas

```
WITH trips AS
   (SELECT t.trip_id, battery_charge_range, dropoff_centroid_location
   FROM vtm.trips t, vtm.trip_details td
   WHERE battery_charge_range < 25.0
   AND t.trip_id = td.trip_id
   AND td.route_time = t.trip_end
   AND td.route_time BETWEEN '2021-08-01' AND '2022-08-01'),
a AS
    (SELECT trip_id, dropoff_centroid_location,
             Min(St_distance(dropoff_centroid_location, St_point(cs.lon, cs.lat), 'MILES')) distance
     FROM vtm.charging_stations cs, trips t
    GROUP BY trip_id, dropoff_centroid_location
    HAVING distance >= 1.0),
v AS
   (SELECT dropoff_centroid_location, St_clusterdbscan(dropoff_centroid_location, 1000, 100)
   OVER () AS b
   FROM a),
z AS
    (SELECT b, st_linestring(Array_agg(dropoff_centroid_location)[:7500]) AS q
    FROM y
    WHERE b!= NULL
    GROUP BY b
    ORDER BY b ASC)
SELECT b.
   st_minimumboundingcircle(q, 100)
FROM z
```



### **CHARGING STATION DESERTS**

AREAS WHERE VEHICLES TEND TO REQUIRE A CHARGE BUT NO LOCAL CHARGING STATIONS EXIST

# THE FUTURE REQUIRES HYPERSCALE ANALYTICS

# Safer, cleaner, more enjoyable driving

### **Automotive Challenges at Hyperscale**

# Autonomous Vehicles

Sensor data centralization and analysis

Map maintenance

Connected car data

# Electric Vehicles

Charging network optimization and delivery

Infrastructure planning

Battery optimization and charging experience

# Delivery and Logistics

Ecosystem of connected products

Data analytics from commercial fleet

Service-area logistical planning

# Safer Driving

Driving pattern analysis

Parts and test data analysis

Driving indicators

### Personalized Experience

Software application usage and trend analysis

Predictive maintenance

# **IN SUMMARY**

What's Required for Innovating at Hyperscale with Geospatial Telematics Data?

(OCIENT)<sup>™</sup>

- Challenges around geospatial data at Hyperscale exist in many industries including government
- Solutions need to be designed and focused on geospatial analytics at Hyperscale
- A **complete geospatial data warehouse** is key to ingest, transform, and analyze data in a single place.
- In-database Machine Learning can reduce the time to value and complexity of moving and transforming large datasets

# **THANK YOU**

For more information about Ocient and geospatial analytics at hyperscale:

visit ocient.com or reach out directly dylanmurphy@ocient.com