DATA+AI SUMMIT
BY databricks

How McDonald's Uses ML to Optimize Site Selection

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06/13/2024

About Us

Enterprise Data, Analytics, & AI at McD

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- Sr. Manager in McD EDAA team
- Interests in machine learning, statistics, and deep learning

Pat Wilkins

- Sr. Manager in McD EDAA team
- Interests in scalable solution architecture, customer & geospatial analytics

What we plan to cover

Advancing McDonald’s ML techniques to support decision -making around new site selection covers several areas

McD as a Real Estate Business

- Accelerate the Arches
- Property & Equipment valued at >$42 billion
- Beginning fastest growth phase in company history

McD leveraging ML/AI across the business

- Problem statement
- Data
- Methodology
- Results

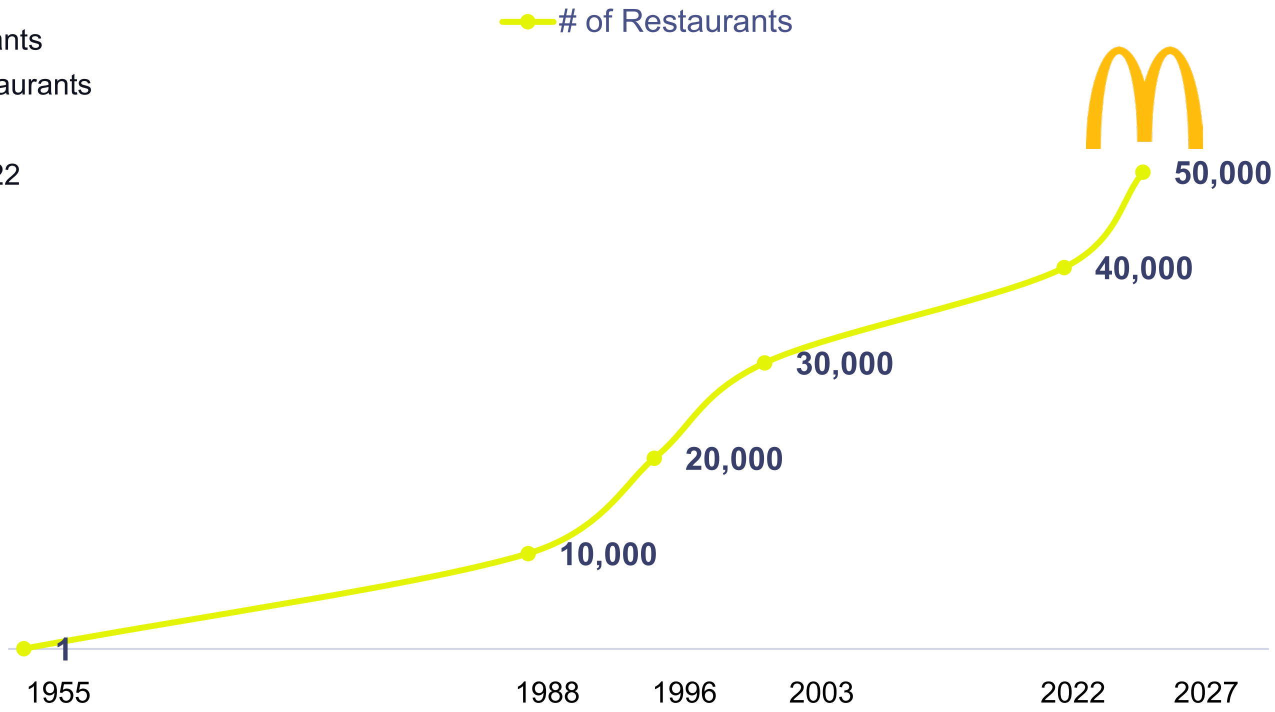
Operating as one McD

- Digital standardization to become more efficient at scale
- First step to quicker innovation

McDonald's from a Real Estate View

McDonald's reaching fastest growth phase in it's history

- 33 years to get to 10,000 restaurants
- 8 years later reached 20,000 restaurants
- 7 more years to reach 30,000
- 40,000 restaurants globally in 2022



Improving site selection analytics

Databricks provides a suitable foundation for successful site selection modeling at scale

Gaps

- Disparate datasets across the globe
- Varying methodologies by market depending on data availability
- Minimal adoption of modern ML techniques

Opportunities

- Standardization of geospatial data
- Introduction of scalable ML approaches
- Operational flexibility to test new data sources over time

Sales Estimation Process

Highlights the history of the real estate development process & sales estimating

Importance

- Minimize missed opportunities
- Ensure high performing stores
- Accurate rental negotiations

Process

- Interviews and surveys
- Location type
- Business
- People
- Accessibility

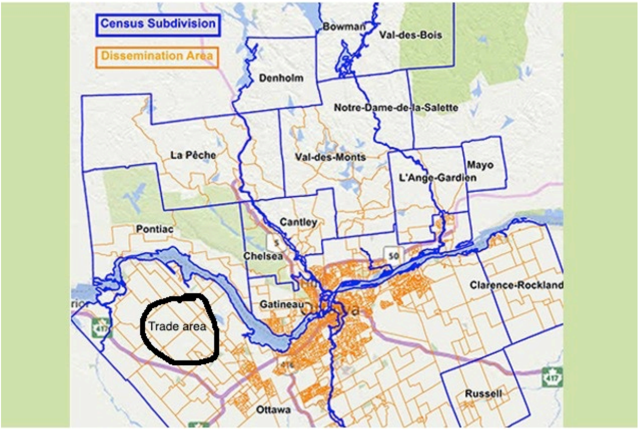
Current limitations

- Opportunities to modernize methodology
- Siloed approach across countries

Key terminology: Trade Area + Gaps

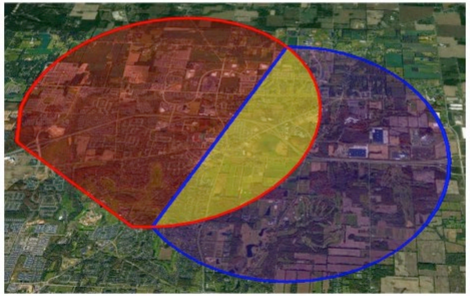
These constructs inform how we analyze and prioritize potential sites

Trade Area is boundary of a potential site that encapsulates most of our potential customers



Gaps identify areas of high potential demand that may be under-served

Objective: Iteratively analyze all demand points in relation to existing restaurants and find those with the largest Net Demand



How to Calculate Net Demand

1. Existing McD Pre-Demand – Existing McD Post Demand = Yellow
2. Gap Demand – Yellow = Net Demand

We leveraged data from map layers

Geospatial .shp files enabled us to represent trade areas comprehensively and at a fine-grained level

Data Sources

Input Data
Road networks
Schools
Population demographics (low level)
Business and QSR competitor
Other "Points of Interest" (POI)

Outcome Data
Yearly Sales (market)

Maps are combination of layers

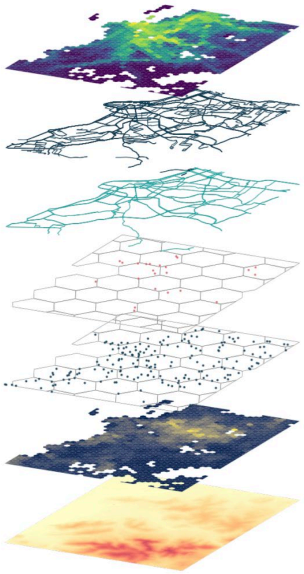
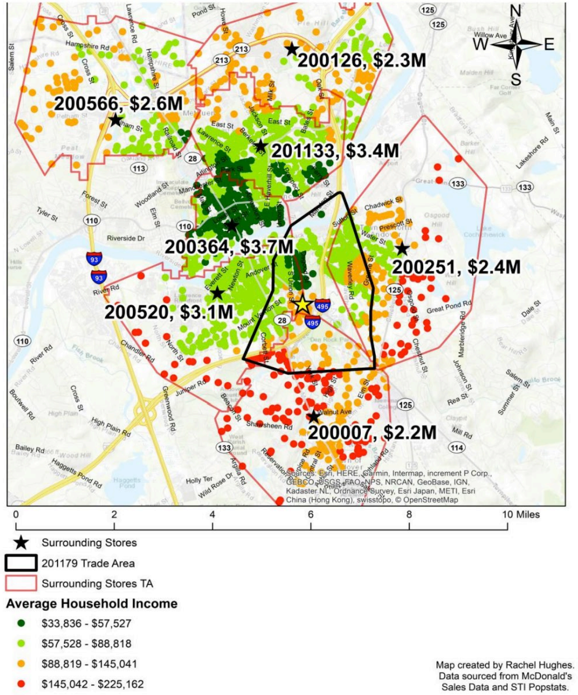


image by @UrbanDemog

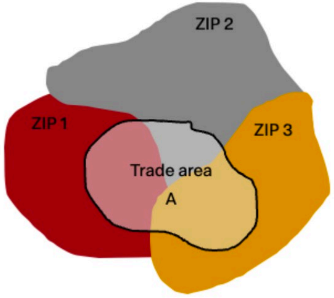
Features rolled up to the trade area level

We applied weighted aggregation techniques to represent trade areas



Trade Area Details

1. Size based on urbanicity and travel time
2. Block features weighted by degree of overlap
3. Decay function down-weighted more distant geographies

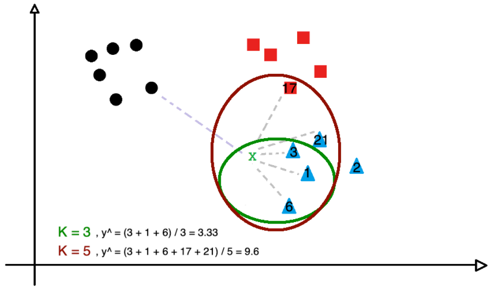


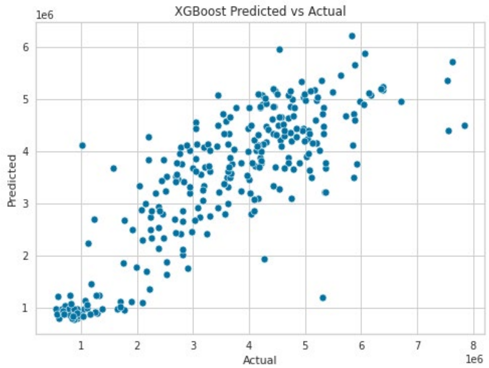
Trade area A = 30% of ZIP 1 + 20% of ZIP2 + 40% of ZIP 3

Modernizing our sales estimation

We tested several algorithms and modeling approaches

- We used stacking as an ensemble approach
- K-Nearest Neighbors algorithm boosted performance with median sales of similar stores
- Achieved over 80% $R2$ on validation and ~78% on test

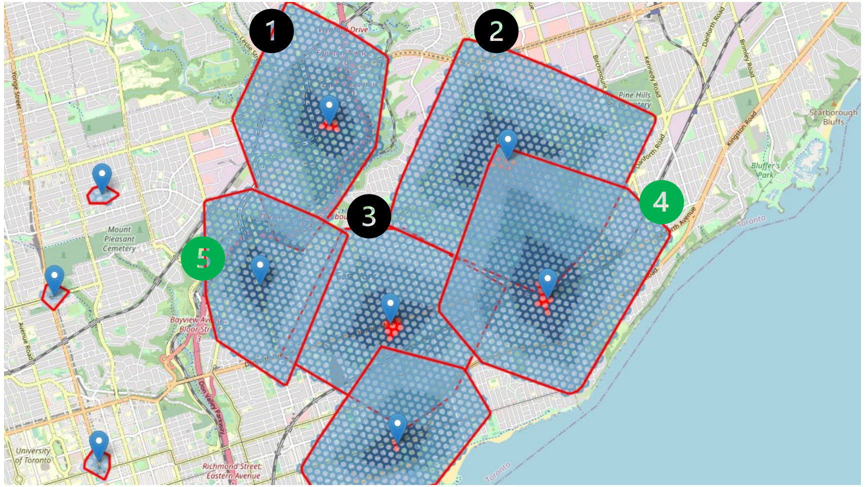




Highlight demand capture and OR

Set covering theory informed the basis of our optimization model

- The optimization considered ML sales output + also other factors to rank by overall projected profitability
- Together the two models formed our end-to-end sales estimation process



Example - Impact of Opening store 5 on Store 1 and Store 3

Revenue1 = 0.8 M

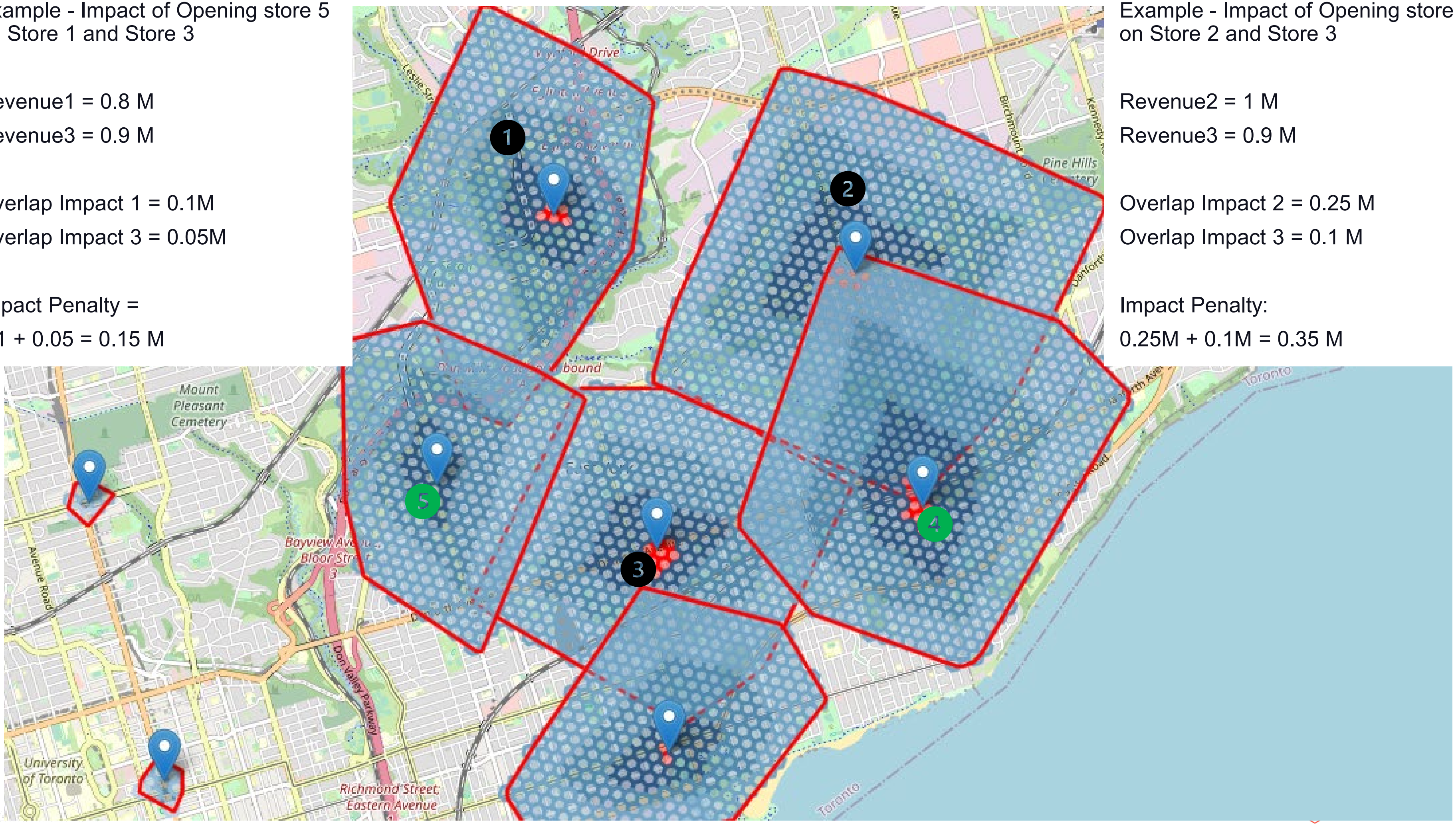
Revenue3 = 0.9 M

Overlap Impact 1 = 0.1M

Overlap Impact 3 = 0.05M

Impact Penalty =

0.1 + 0.05 = 0.15 M



Example - Impact of Opening store 4 on Store 2 and Store 3

Revenue2 = 1 M

Revenue3 = 0.9 M

Overlap Impact 2 = 0.25 M

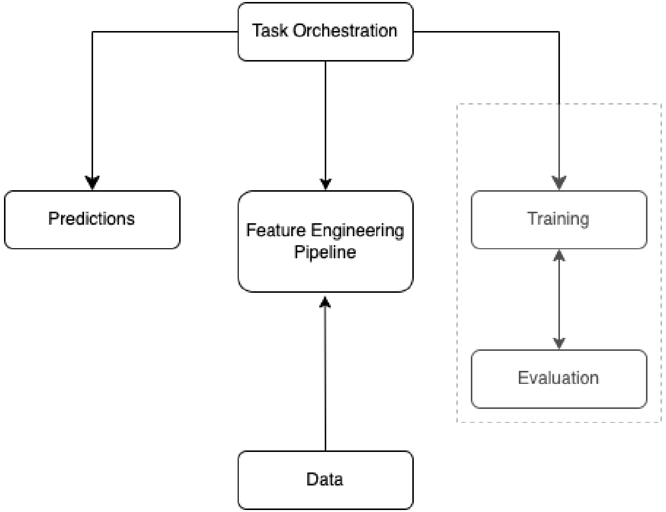
Overlap Impact 3 = 0.1 M

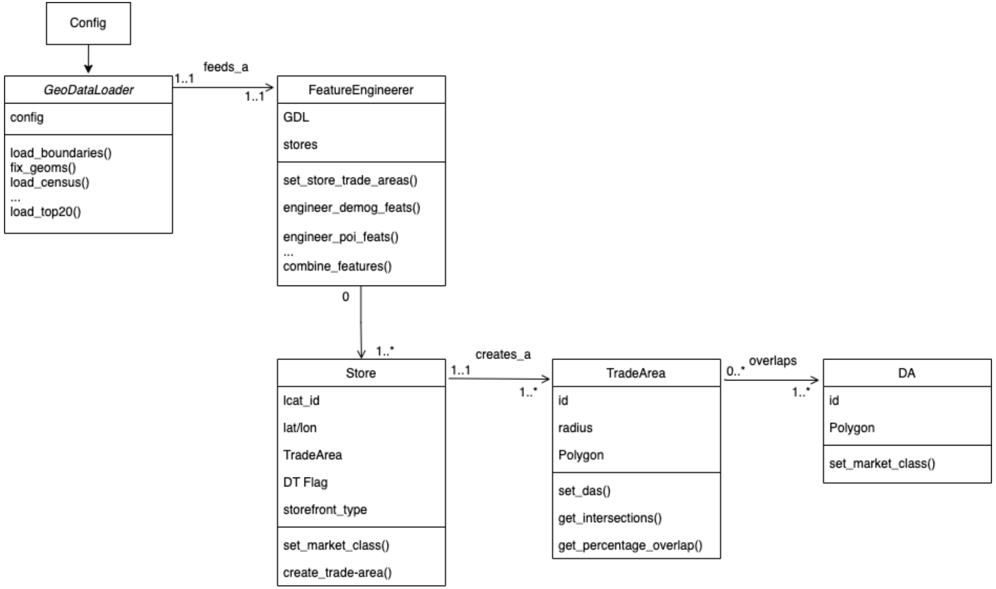
Impact Penalty:

0.25M + 0.1M = 0.35 M

Model Outcomes

After POC, we built a workflow to support scaling to multiple markets





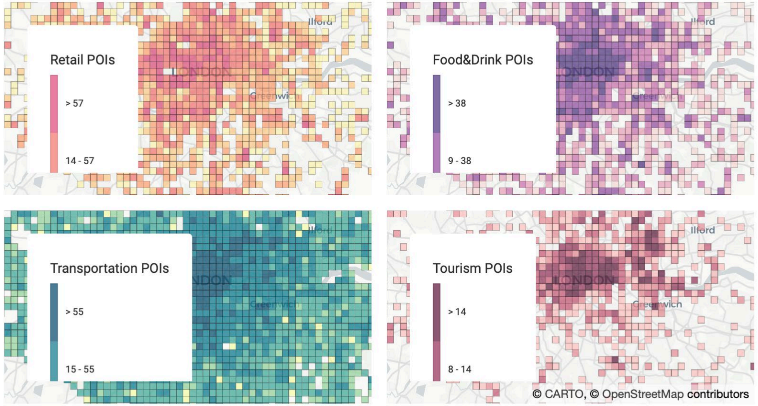
Unifying Analytics

Varying geospatial data across the McDonald's markets

	Demographics	Mobility	Points of Interest	Traffic	Competitor Data	Customer Segmentation
Country 1	x	x	x		x	
Country 2		x		x	x	x
….						
Country 118	x		x		x	x

Enhancements: Databricks Marketplace

Improving ROI on 3rd Party Data Assets



geospatial | Product | Provider

249 results for "geospatial"

Databricks Marketplace >

Spatial Features (Spain, H3 Res. 8)

CARTO

Tables Free

Overview

Spatial Features is a dataset curated by CARTO providing access to a set of location-based features with global coverage that have been unified in common geographic supports (eg. H3). This product has been specially designed to facilitate spatial modeling at scale.

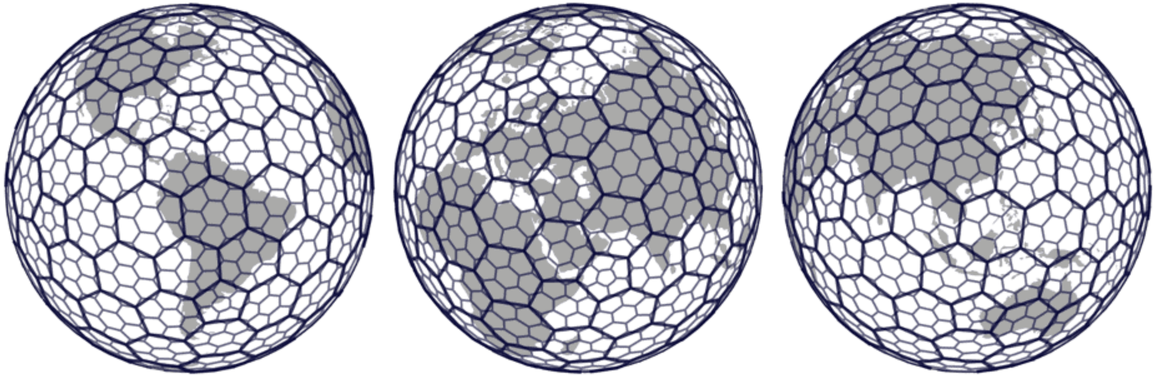
Spatial Features includes core demographic and environmental data, and POI aggregations by category that have been generated by processing and unifying globally available sources such as Worldpop, OpenStreetMap, Nasa and Worldclim.

The current version of this product is available in three different spatial aggregations: Quadgrid level 15 (with cells of approximately 1x1km), Quadgrid level 18 (with cells of approximately 100x100m) and H3 resolution 8 (hexagon cells of approximately 0.7 sqkm).

Enhancements: H3 support

Databricks support of H3 geospatial processing & analytics provides a framework for standardized analytics at scale

- As an open-source system, H3 has become a sort of de facto standard.
- H3 system can be useful for **standardizing analyses across projects within an organization.**



Summary & Takeaways

Modern data science methods provide an increase in business value

- Worth our time to exercise thoughtful approaches to data collection and feature engineering
- Combining machine learning and optimization techniques helped us to deliver on the full business ask
- Databricks enabled easy experimentation and scalable codebase development

Adopting enterprise wide change requires a long-term approach

- The first step towards a modern enterprise level approach was showcasing sales estimation accuracy of ML methods
- Standardization & centralization of relevant data assets will accelerate the scaling of these methods globally