Geospatial and Temporal Forecasting at Uber

September 09, 2019

Apachecon

Chong Sun, Brian Tang

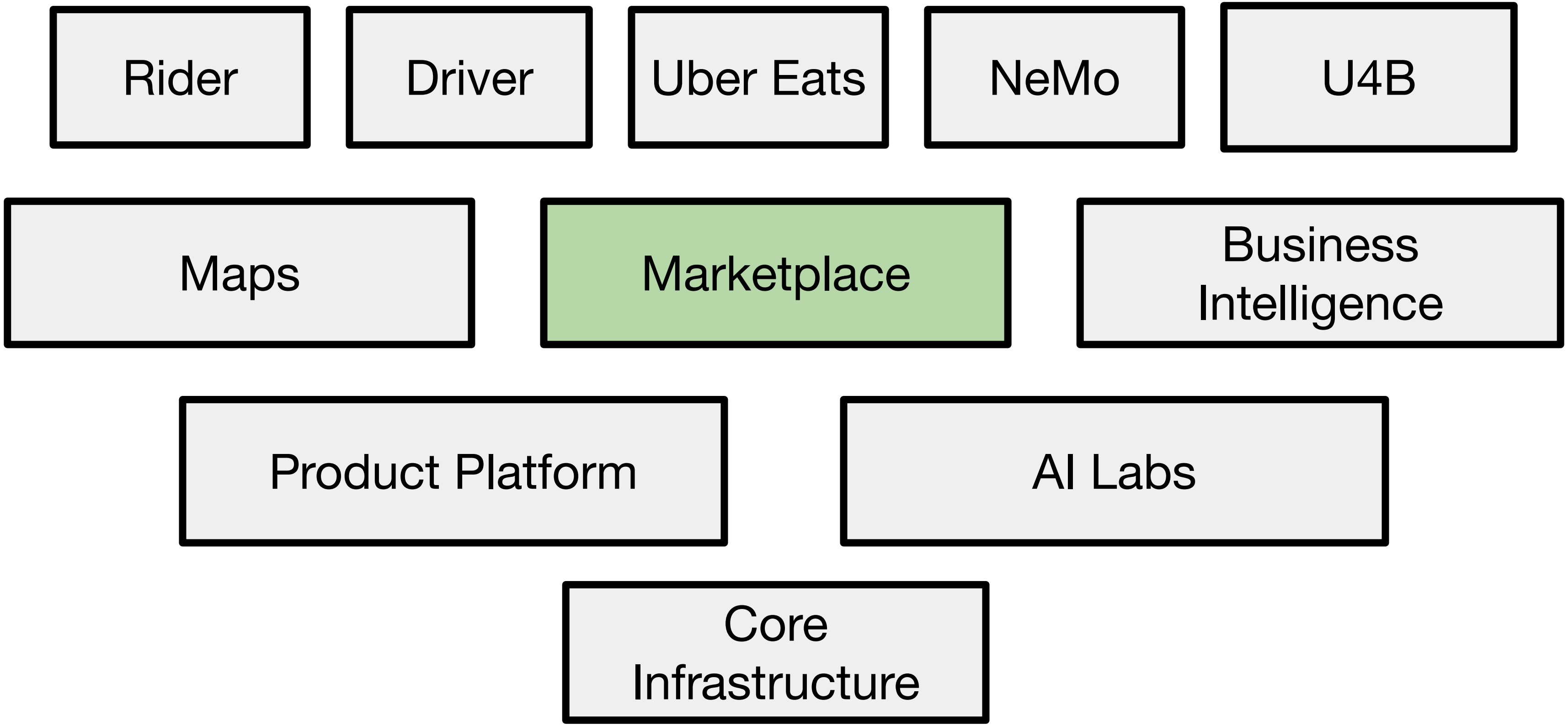
Uber

01 Marketplace Forecasting at Uber
02 Geospatial Representation
03 Geospatial Processing
04 Use Cases

Marketplace Forecasting at Uber

What is marketplace and how does forecasting fit in?

Uber Marketplace



Marketplace Forecasting

Real Time Forecasting

Minute-level forecasts 1- 2 hours into the future

Near-Term Forecasting

10-15 minute-level forecasts several hours into the future

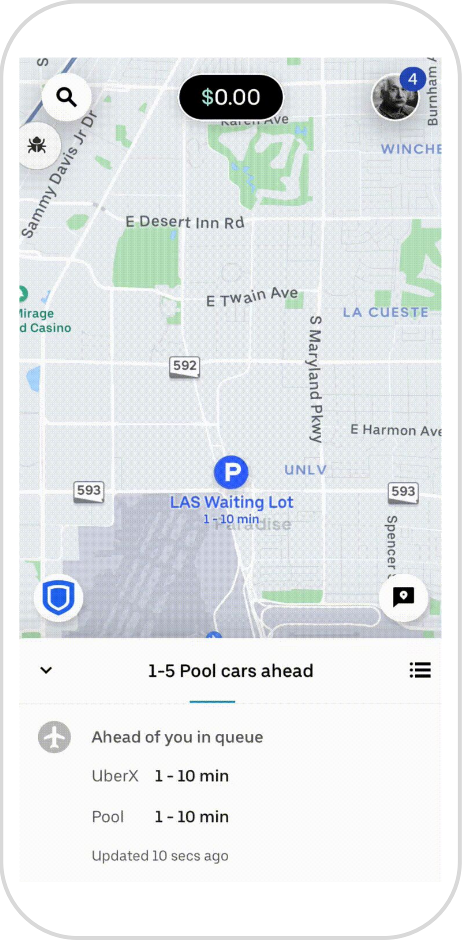
Long Term Forecasting

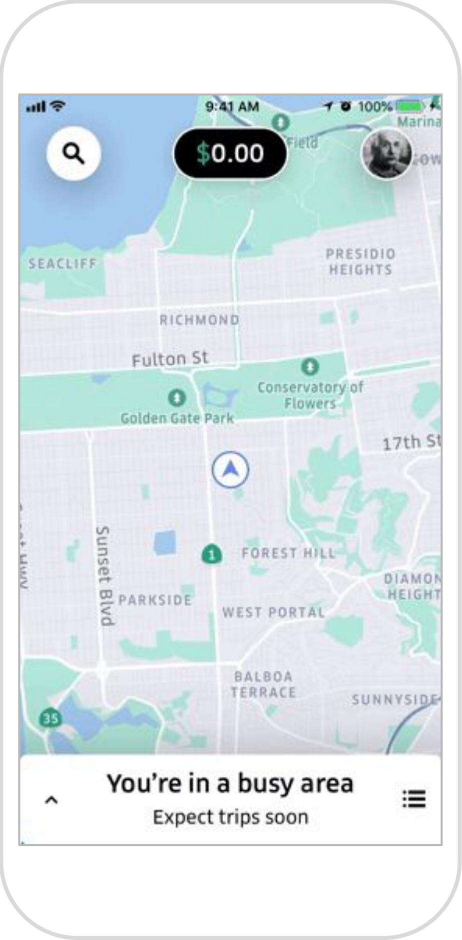
Hour level forecasts 1-2 weeks into the future

Estimated Time to Request

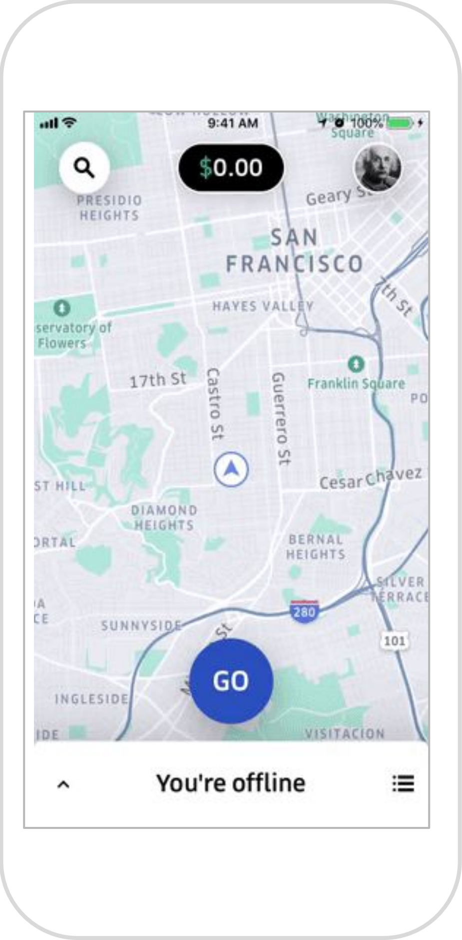
Help drivers decide if they should wait

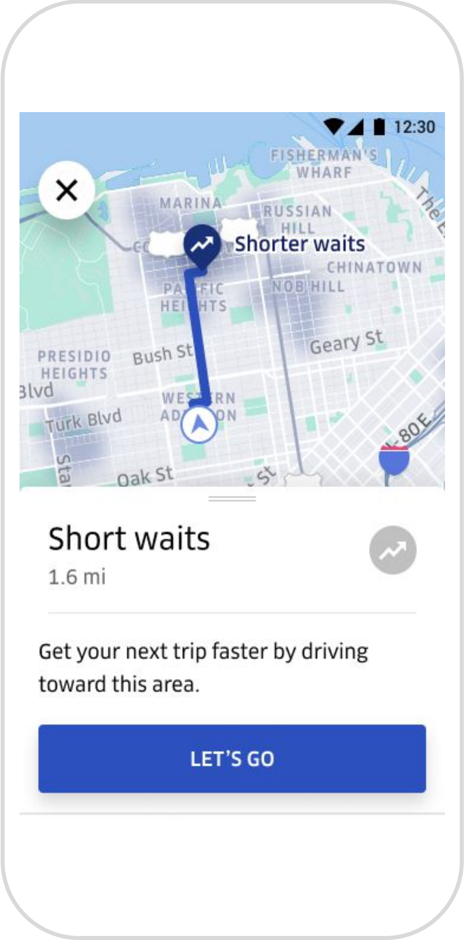
Use historical and recent signals to predict the future wait times across cities and airports.





Suggestions





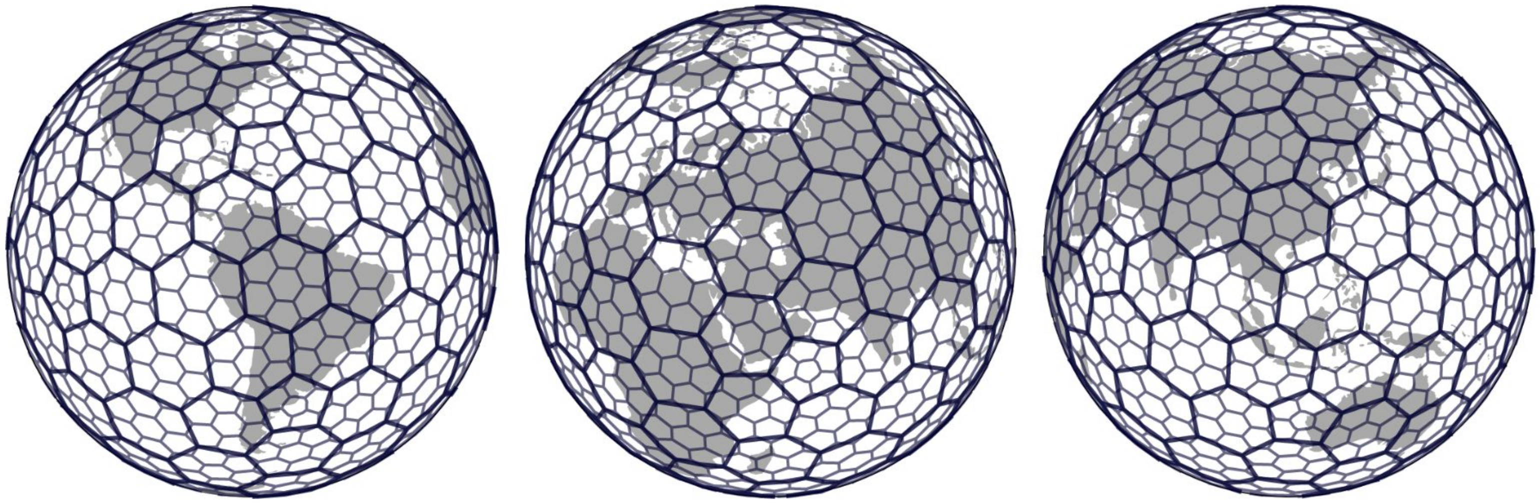
Help drivers decide if they should move

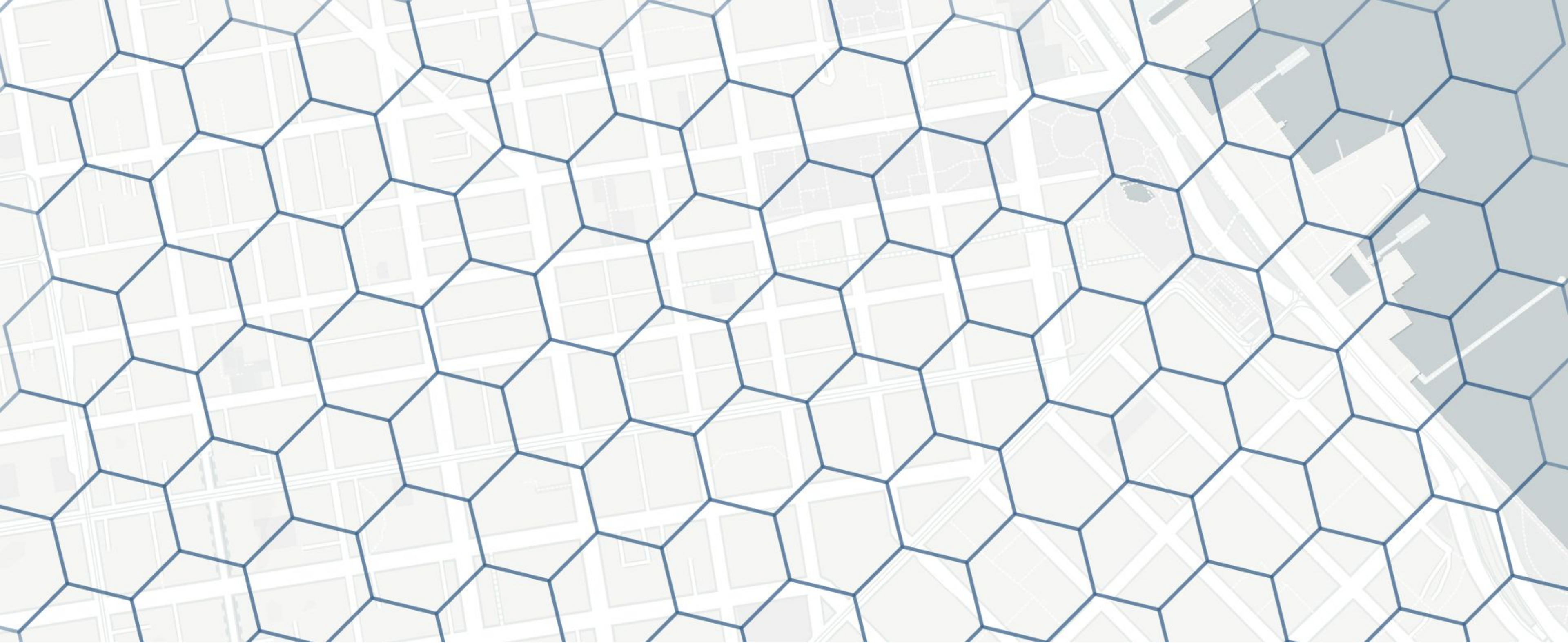
Suggest locations with more opportunities for matching with riders and help them navigate there

Geospatial Representation

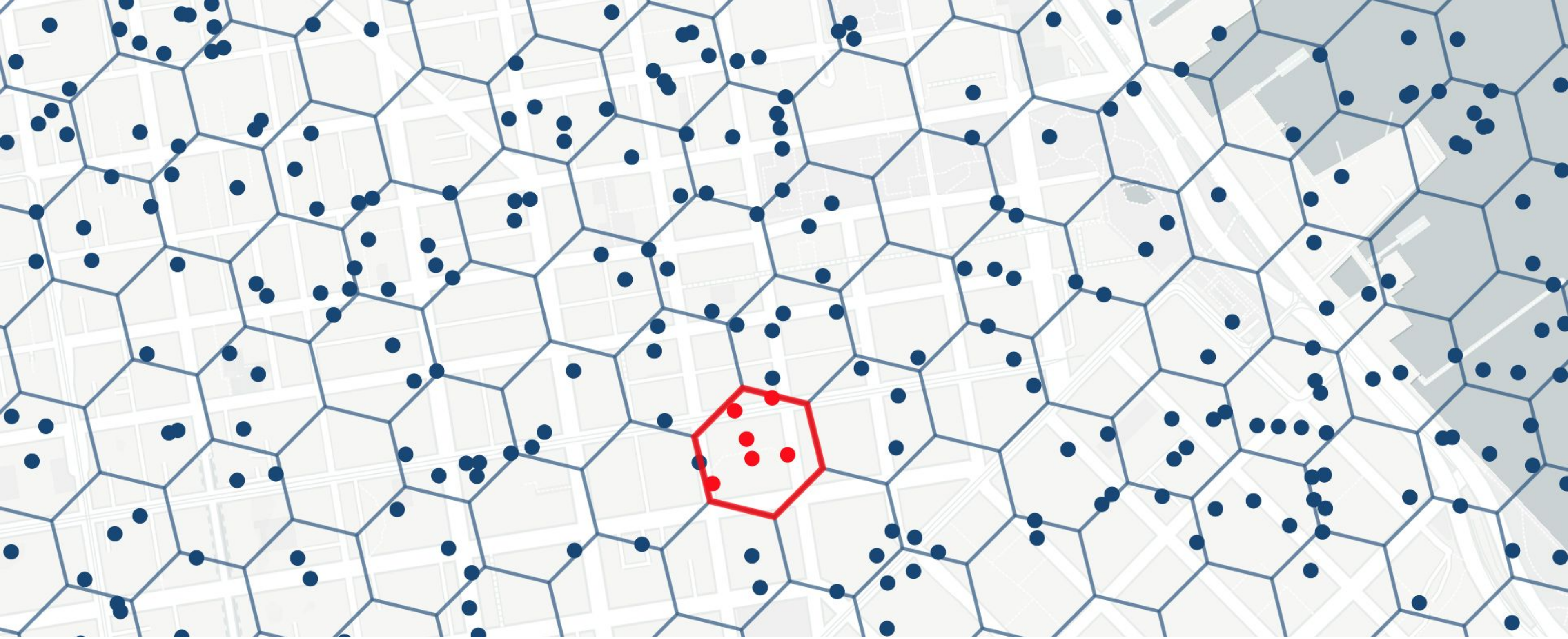
How does Uber see the world?

Hexagons!

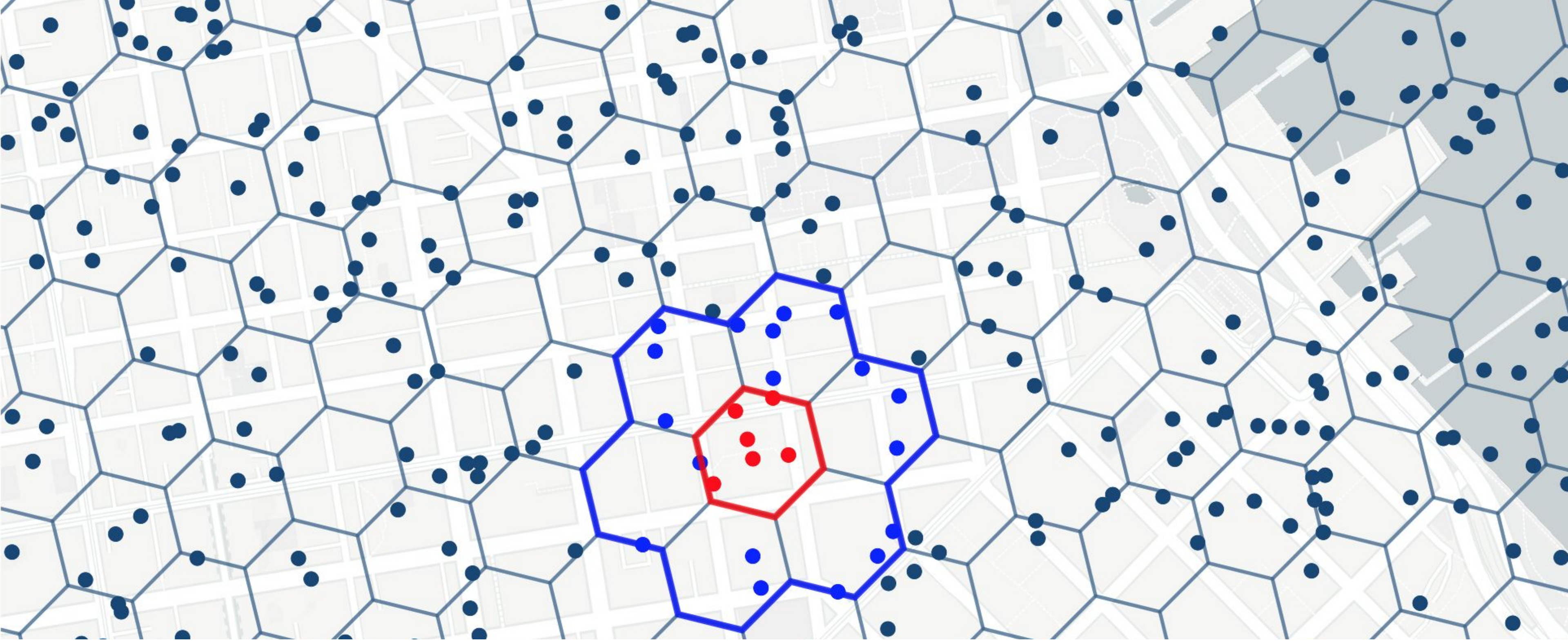




Partition the world

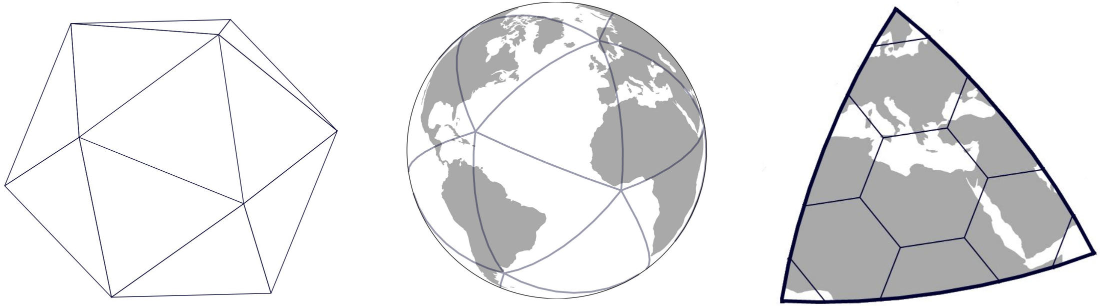


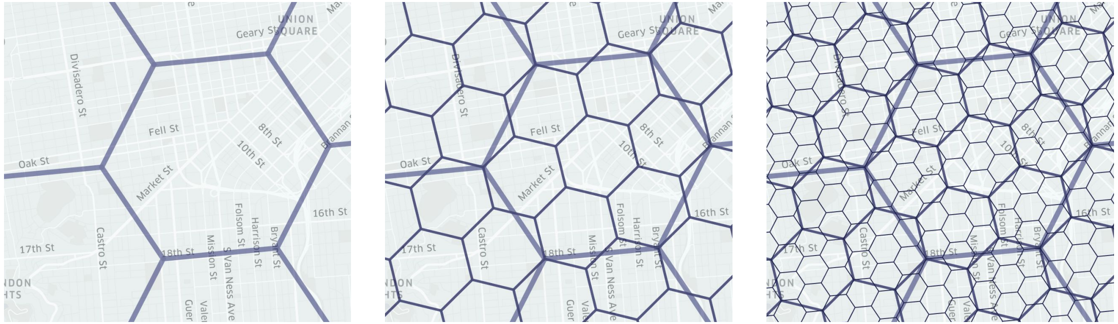
Index data



Run algorithms

H3

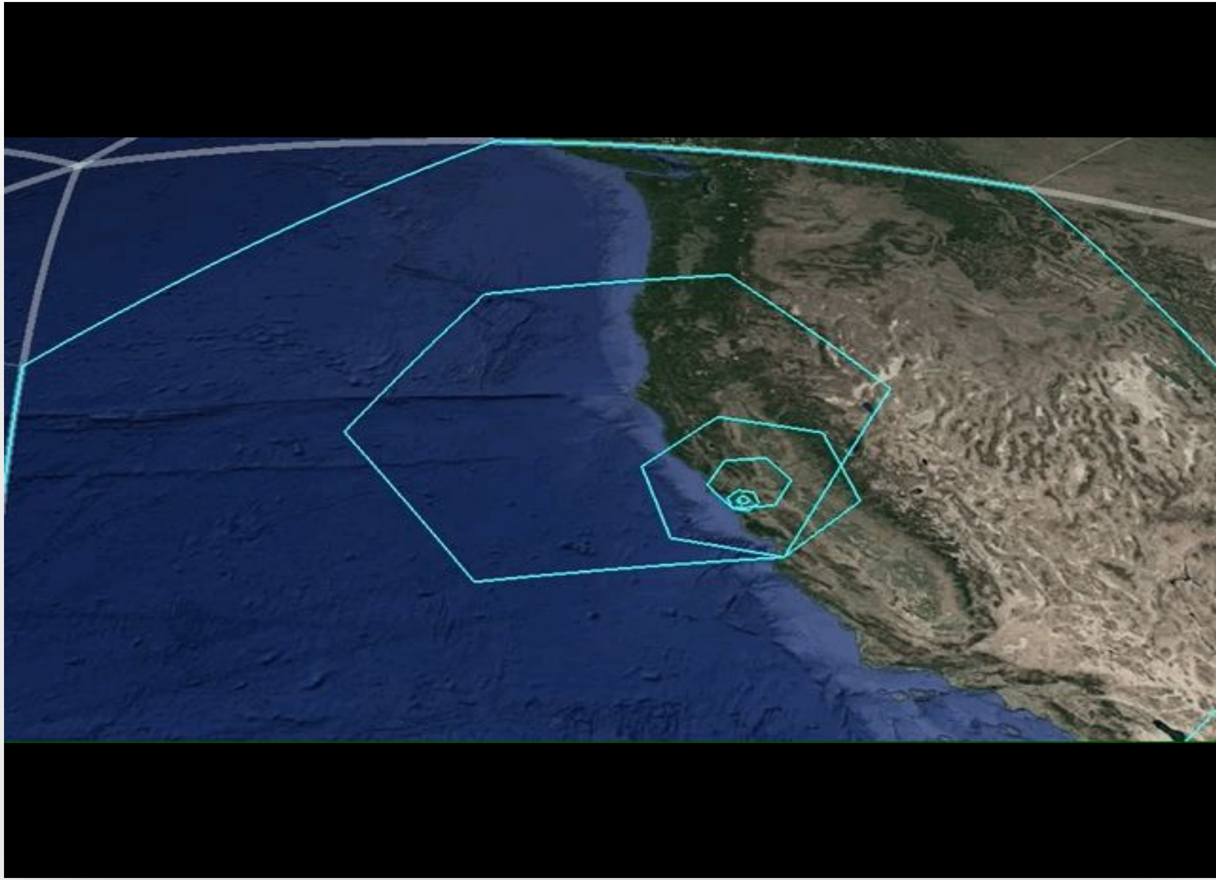




Hexagonal Hierarchical Geospatial Indexing System

H3 is an [open source]() geospatial indexing system using a hexagonal grid that can be (approximately) subdivided into finer and finer hexagonal grids, combining the benefits of a hexagonal grid with S2's hierarchical subdivisions.

H3 Resolutions

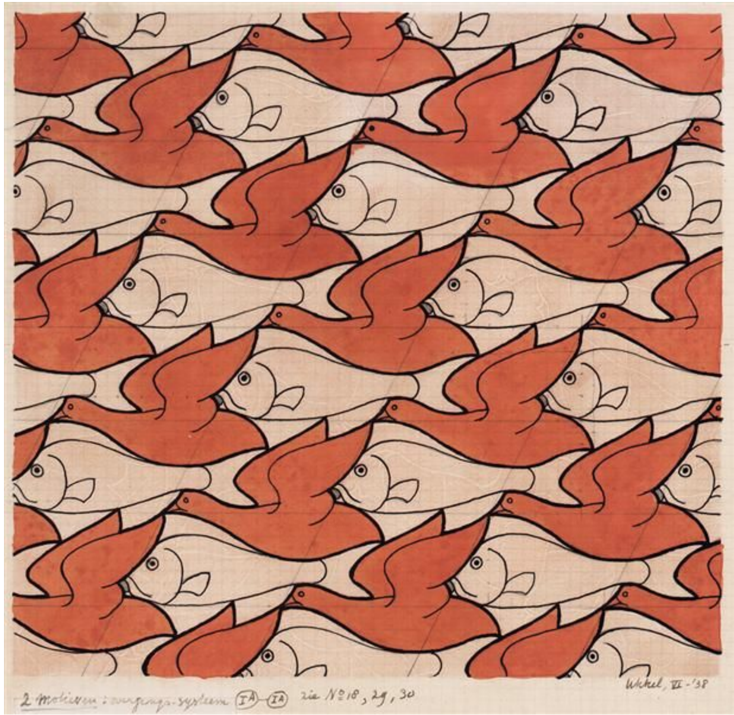


Hierarchical subdivisions

With the largest resolution roughly the size of continents down to the smallest resolution of a meter squared. The library gives flexibility in the size of hexagon to work with

Data SIO, NOAA, U.S. Navy, NGA, GEBCO,
Image Landsat / Copernicus
Image IBCAO

Why hexagons?



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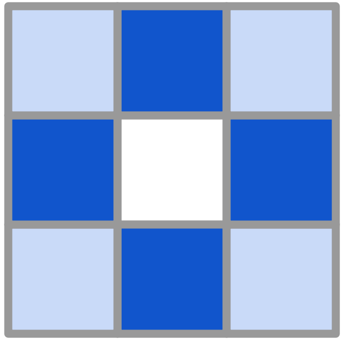
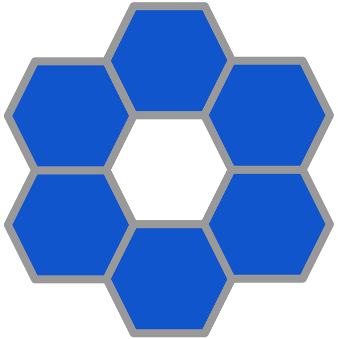
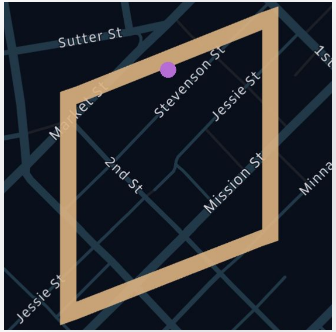
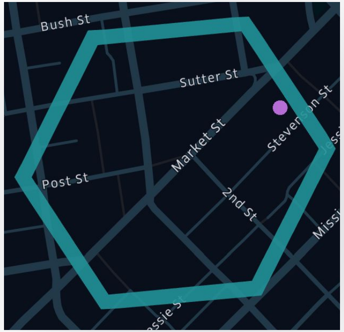




Uniform adjacency

Hexagons have no ambiguous neighbors





Low shape and area distortion

Hexagons can fill an icosahedron and offer low distortion

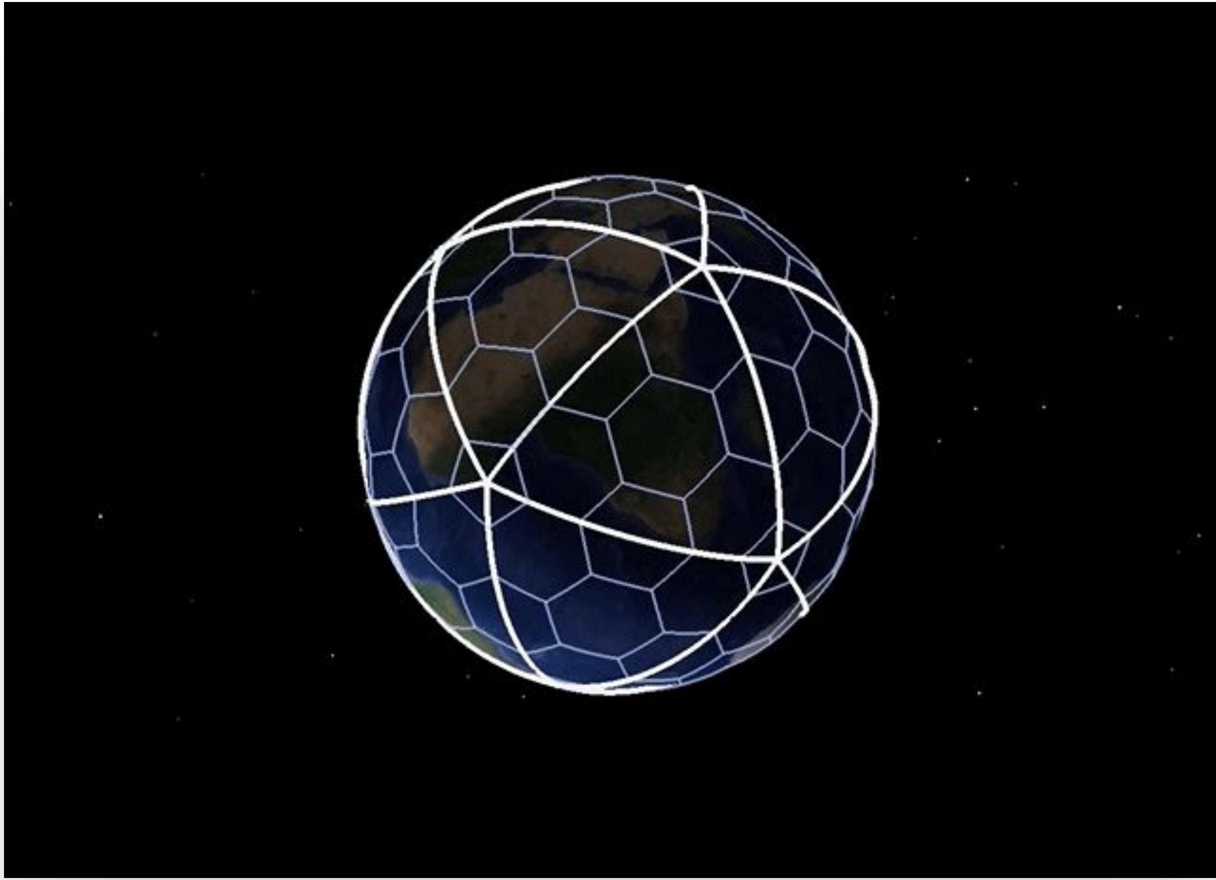
Global Grid

Few tradeoffs

- Not completely uniform shape
- Not perfect child containment

Many advantages

- Uniform edge length
- Uniform angles
- Optimally compact
- Optimally space-filling
- Uniform adjacency
- Hierarchical relationships
- Low shape distortion
- Low area distortion



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Geospatial Processing

Working with hexagons

Hexagon Data

Uber on Hexagons

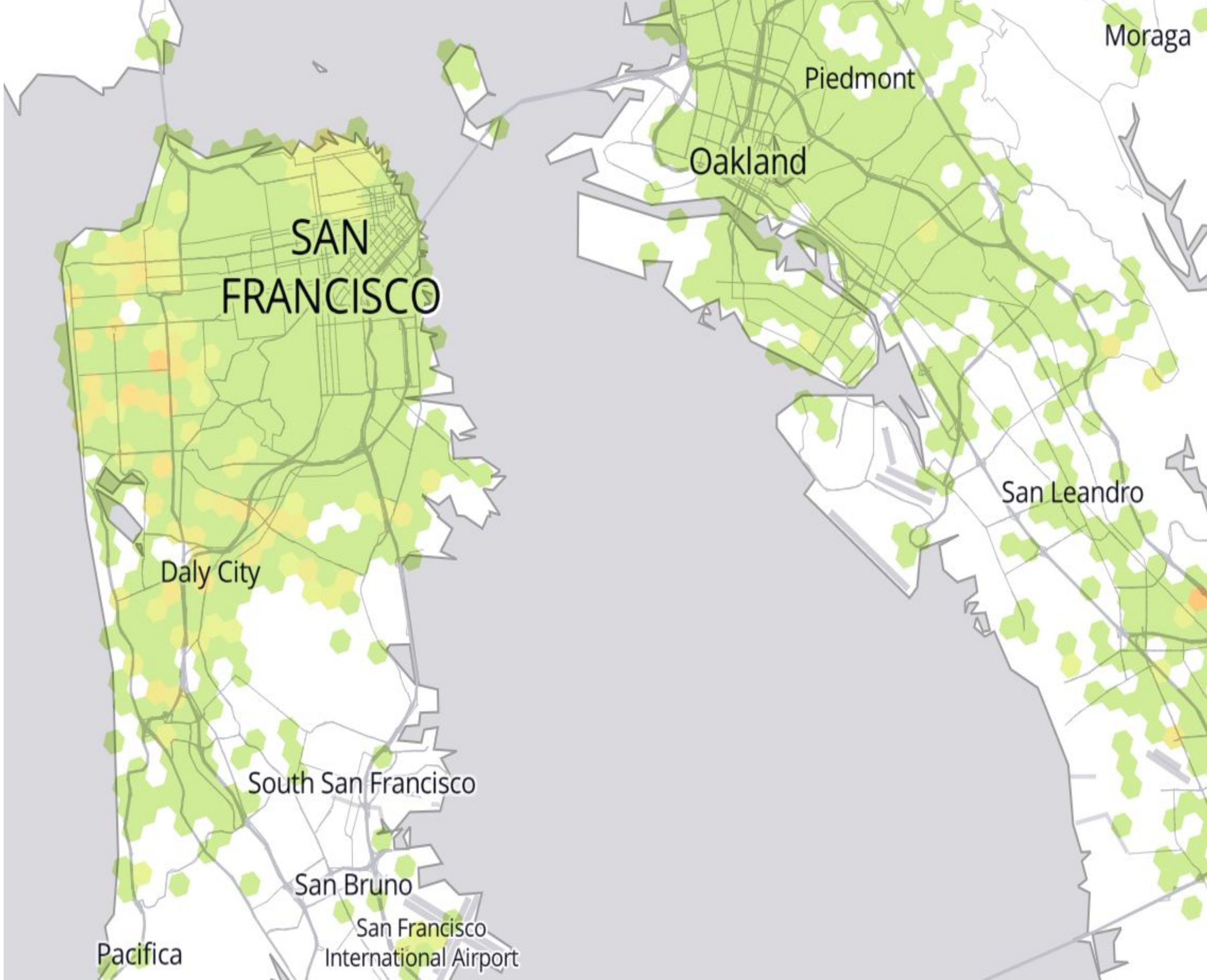
Many decisions are made on small hexagons

Hexagons Level 9

Larger cities have 500k+ hexagons

Sparse Data

E.g., a few requests in some hexagons for a whole day



Hexagon Data Smoothing

Hexcluster

Clustering hexagons into groups and use the aggregated values of all the hexagons in each cluster

- Low computation
- “Arbitrary” boundaries

Kring smoothing

For each hexagon, using the aggregated values of all its k ring neighbours

- Heavy computation
- Flexible

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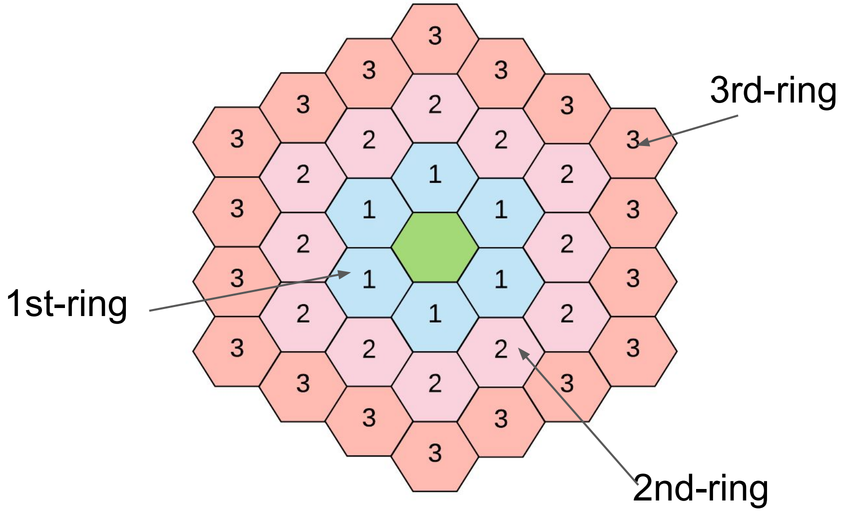

	# hexagons
1-ring	6
2-ring	12
3-ring	18
k-ring	6 * k

M hexagons **K**-ring data smoothing computation:

M* K * (6 + K*6) / 2

Convolution

Input Matrix

1	0	1	0	1
2	1	2	0	3
2	3	1	0	2
0	1	0	2	1
3	2	0	1	0

Kernel/Filter

1	1	1
0	0	0
1	1	1

Output Matrix

8	5	5
6	6	8
11	7	4

(2-D) Convolution

Slide a kernel (small matrix) on top of an input (big matrix), multiple and add the corresponding values to produce the convolution result.

A base component of CNN (Convolutional Neural Network) in deep learning.

Efficient Implementation

Many efficient implementations of convolution in popular packages, e.g., Scipy, TensorFlow, PyTorch.

GPU Acceleration

GPU is a perfect fit for accelerating convolution computation.

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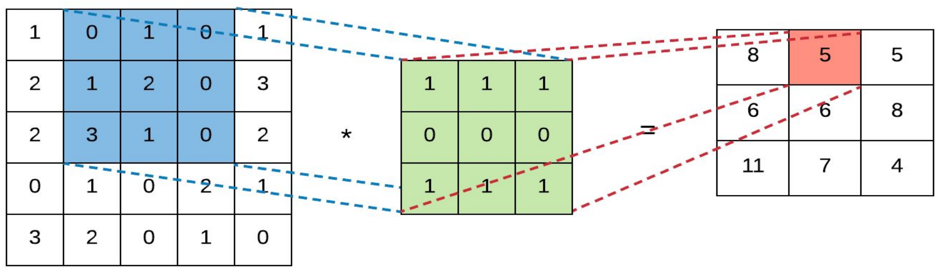

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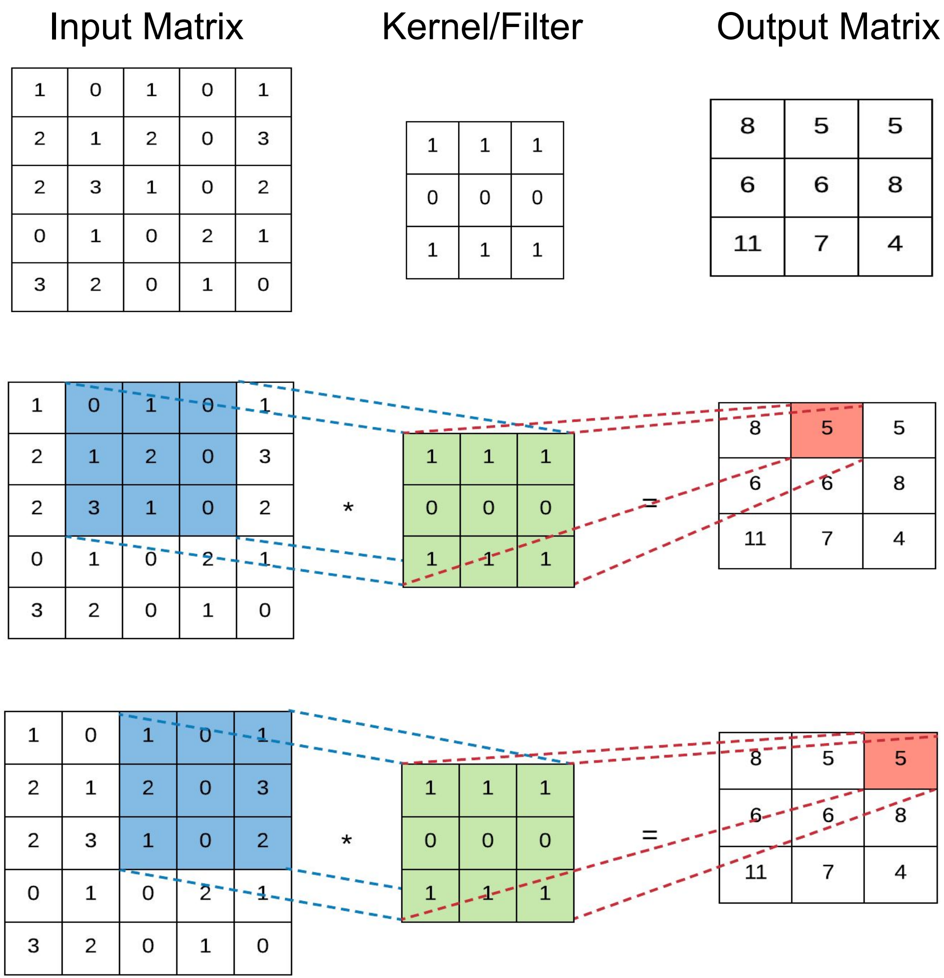

Hexagon Convolution

Hex Convolution

Conceptually, convolution on hex is similar to convolution on square grid matrix

Filter

Using different weights in the filter generates different convolution results. E.g., weighted sum.

Kring data smoothing could be done by using convolution with weight 1 for each hexagon of K rings, e.g, 1-ring smoothing

Challenge

None of known convolution implementations is for hexagon coordinate systems

Optimization and GPU acceleration could not be applied to hexagons directly

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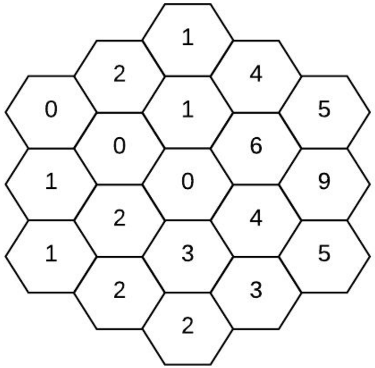
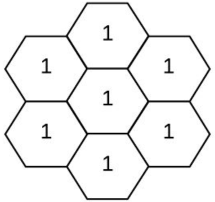
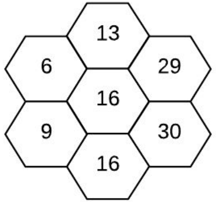


Kernel/Filter
(Equal Weight)



Output



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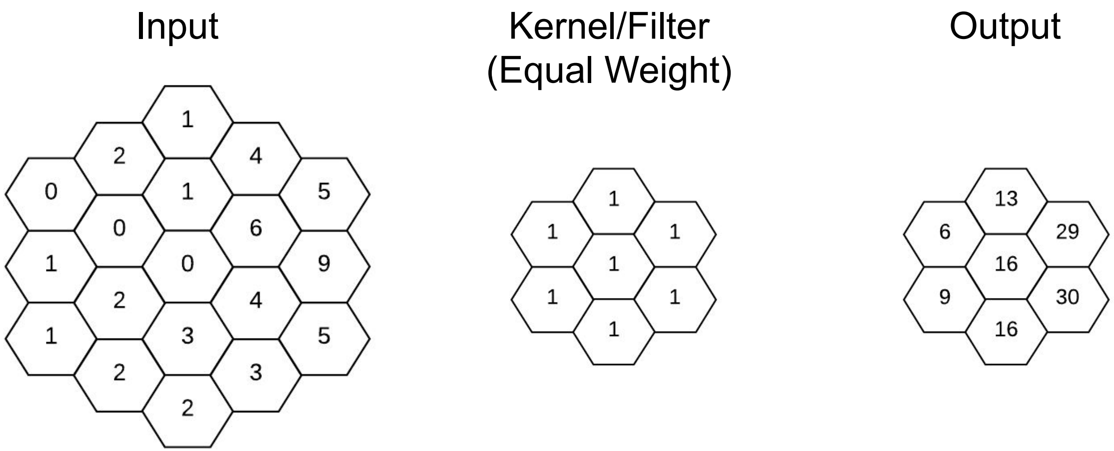
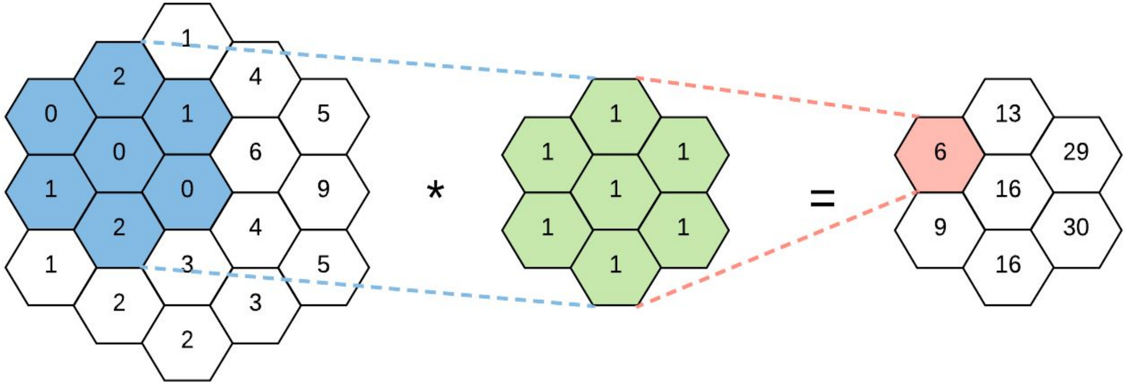
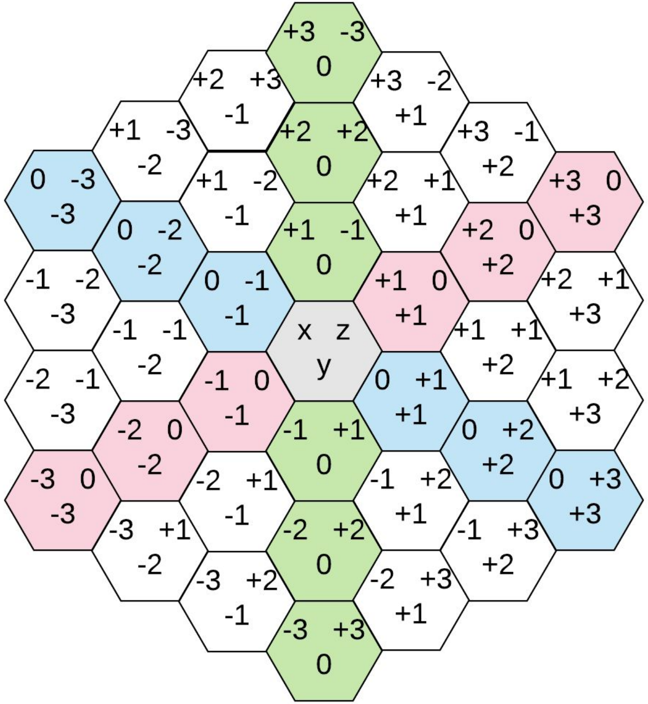




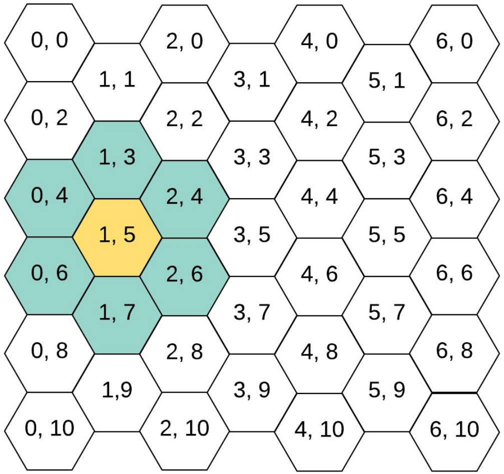
Hexagon Coordinate System (1)

Cube Coordinate

- Represents 2-D hexagon grid in a 3-D Cube.
- Memory inefficient
- No direct map from cube coordinate to a 2-D rectangular grid



Hexagon Coordinate System (2)



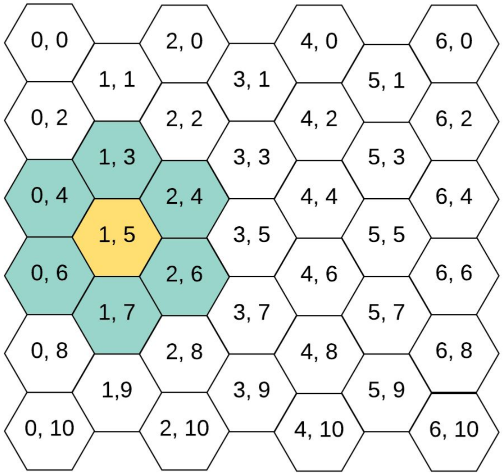
Double Coordinate

- Two double coordinates
  - Double coordinates by heights (example)
  - Double coordinates by widths

- Easy map to square grid based on the coordinate values

- Very inefficiency for convolution as the cells are not contiguous

Hexagon Coordinate System (2)



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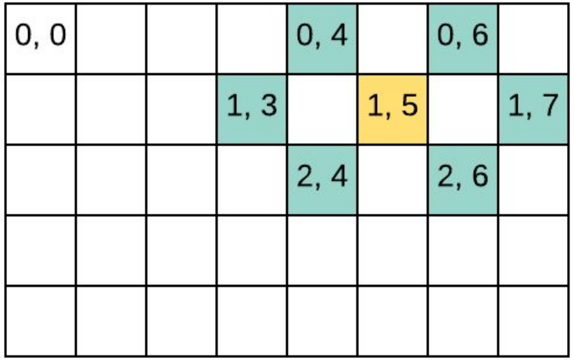
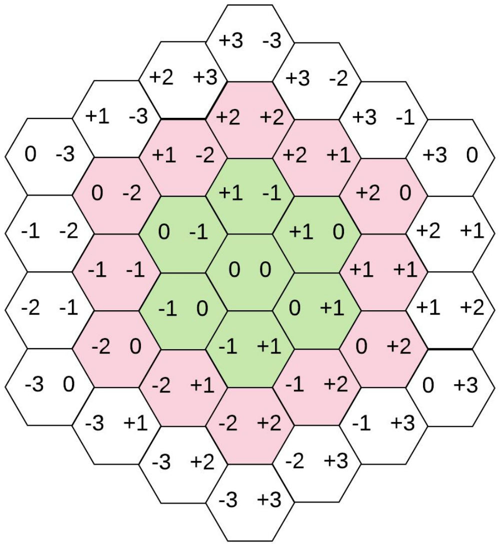


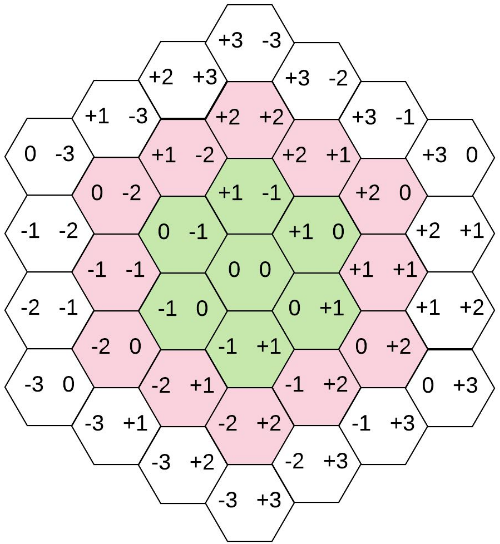
Hexagon Coordinate System (3)



Axial Coordinate

- Map to the square grid well with missing cells in the corner
- Good fit for the convolution with extra filtering

Hexagon Coordinate System (3)



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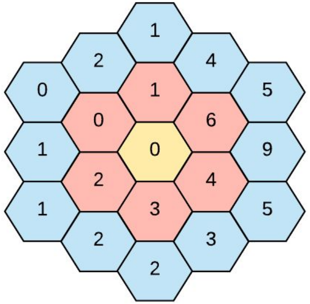
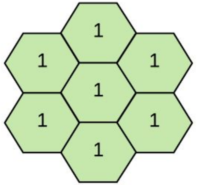
			-2, 0	-2, +1	-2, +2	
		-1, -1	-1, 0	-1, +1	-1, +2	
	0, -2	0, -1	0, 0	0, +1	0, +2	
	+1, -2	+1, -1	+1, 0	+1,+1		
	+2, -2	+2, -1	+2, 0			

Hexagon Convolution (0)

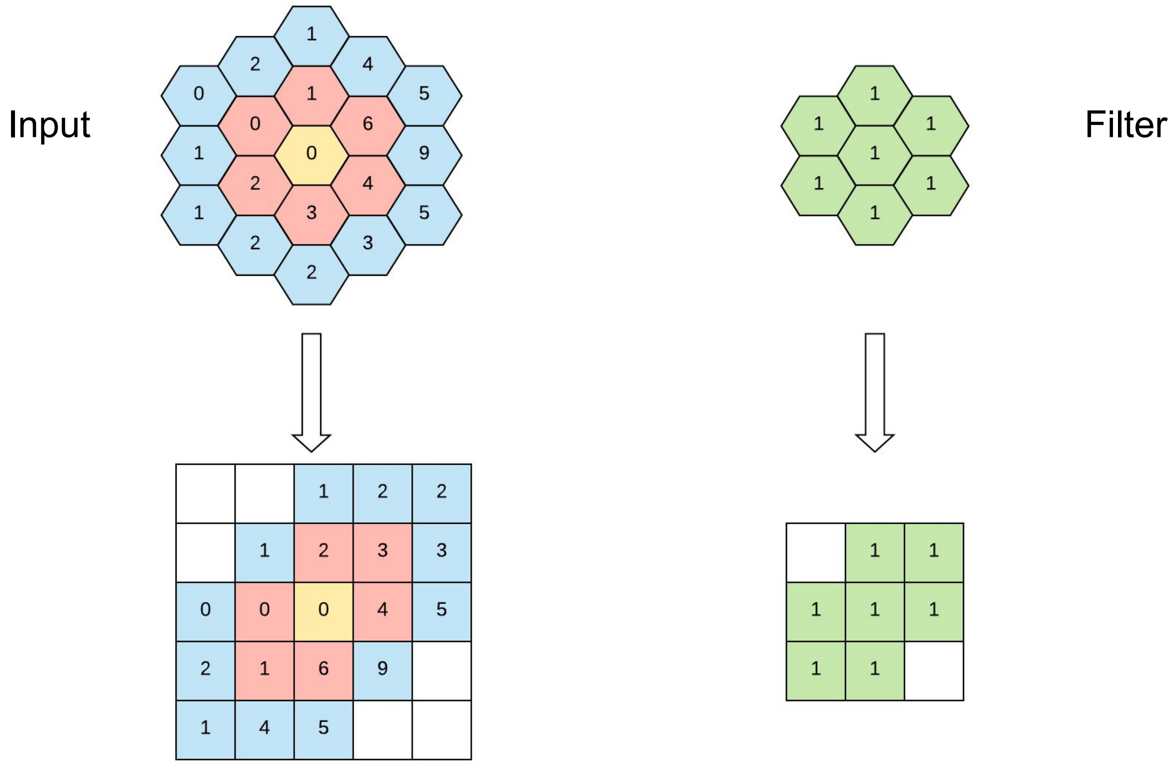
Input



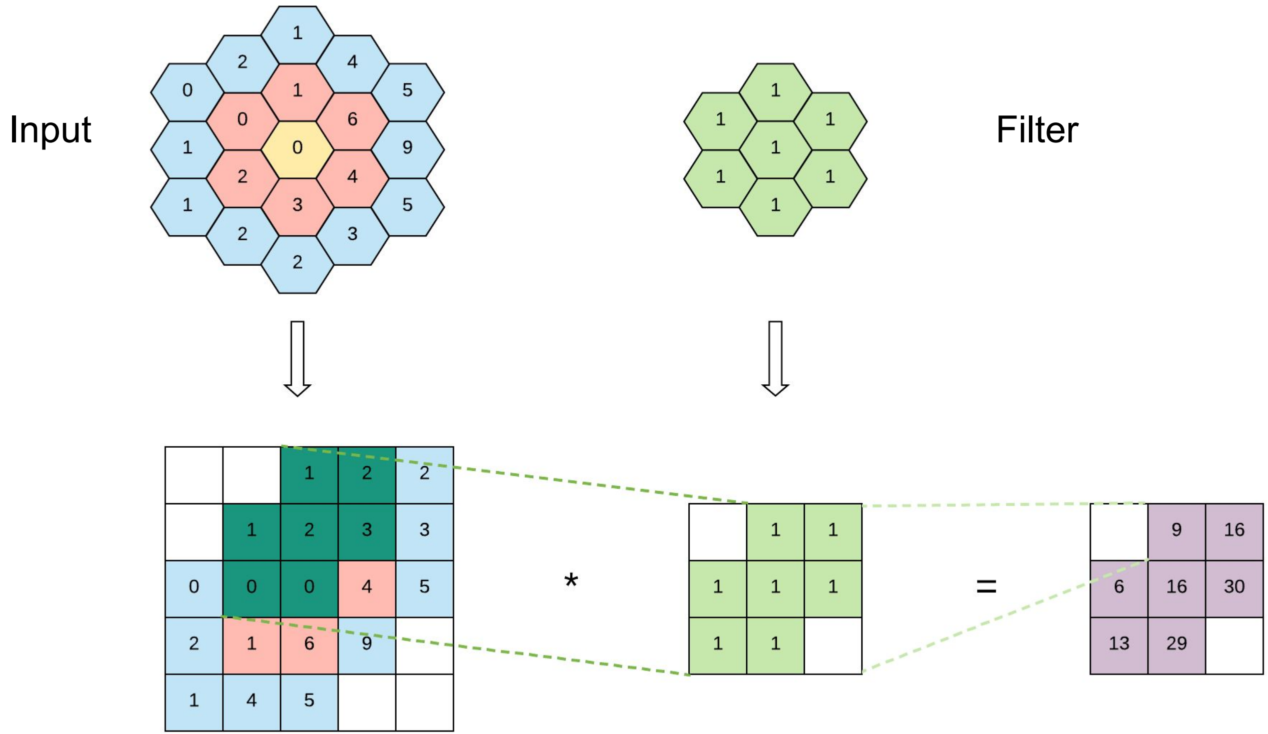


Filter

Hexagon Convolution (1)



Hexagon Convolution (2)



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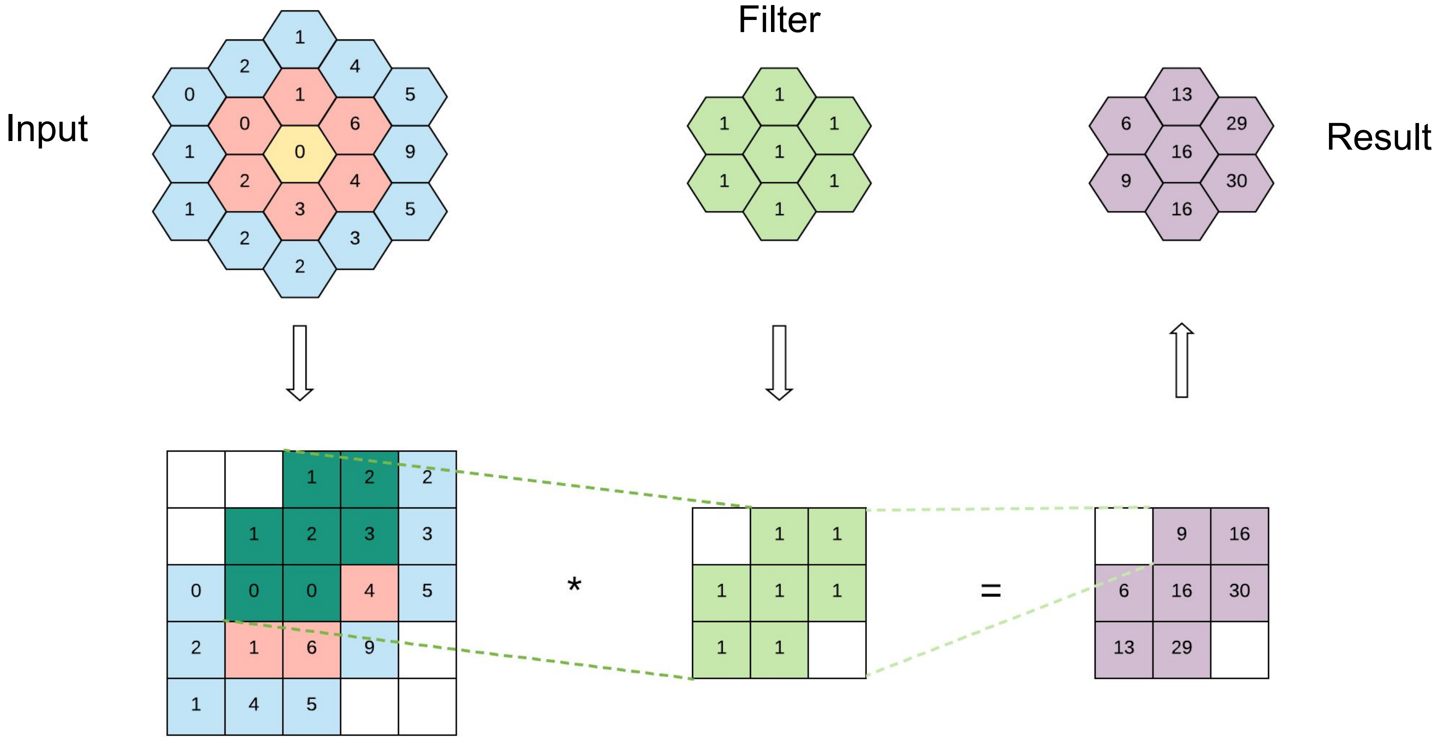
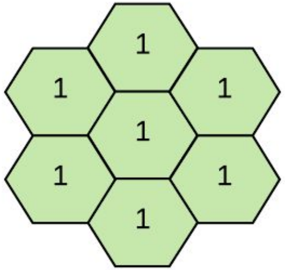
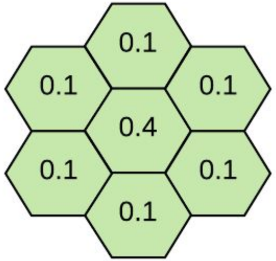


Kring Data Smoothing



Equal Weights



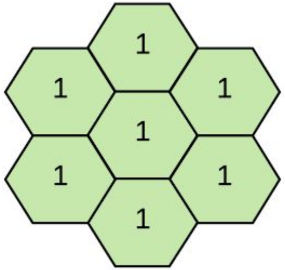
Dynamic Weights

Kring Data Smoothing

Smoothing hexagon data with values in kring the neighbour hexagons.

- Weights for kring smoothing
  - Equal weight kring smoothing
  - Dynamic weight kring smoothing
- Dynamic kring size for smoothing
  - Run the smoothing for all the kring sizes separately

Kring Data Smoothing



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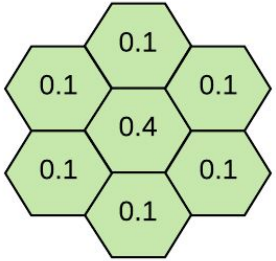

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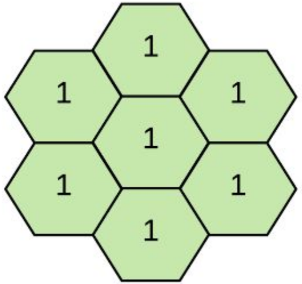
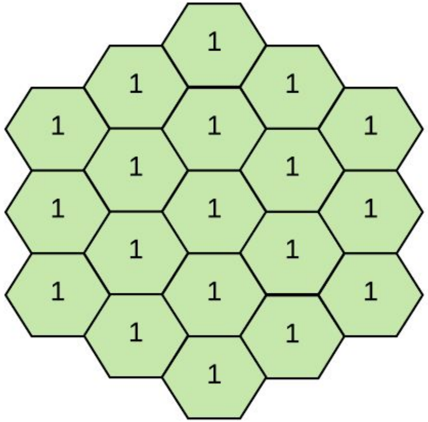


Kring Size 1



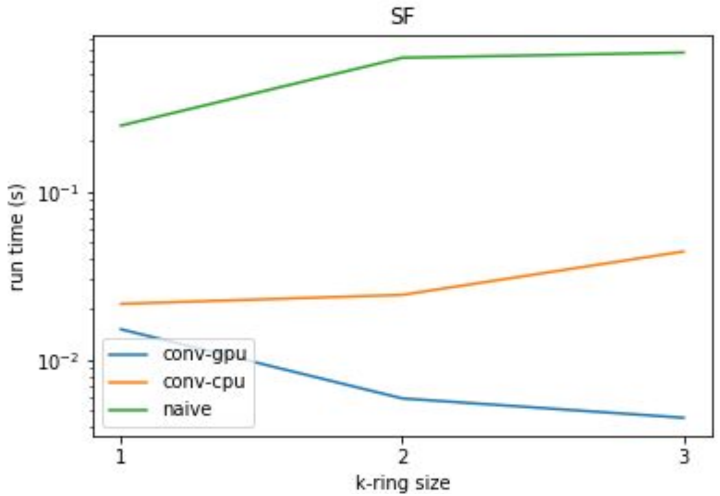
Kring Size 2

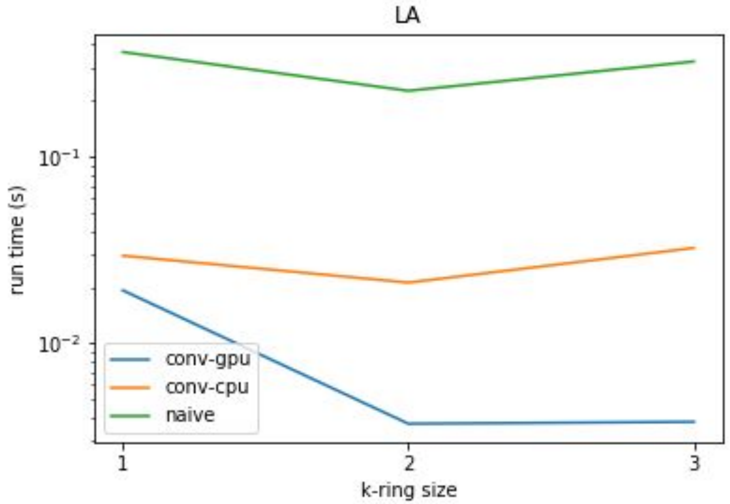
Kring Smoothing Performance

Performance Comparison

- Basic implementation
- Convolution approach with CPU
- Convolution approach with GPU

100x faster than k-ring smoothing with GPU and 10X faster with CPU





Use cases

How is this used in production?

Every minute

30M+	700+	10+
Hexagons smoothed and forecasted	Cities worldwide	Quantities forecasted

Flink

High throughput and low latency

Developed as a true streaming framework from the ground up, Flink has enabled us to produce forecasts with only a few seconds of latency

Efficient memory management

Even with complex custom aggregations we have been able to keep memory utilization under 60%

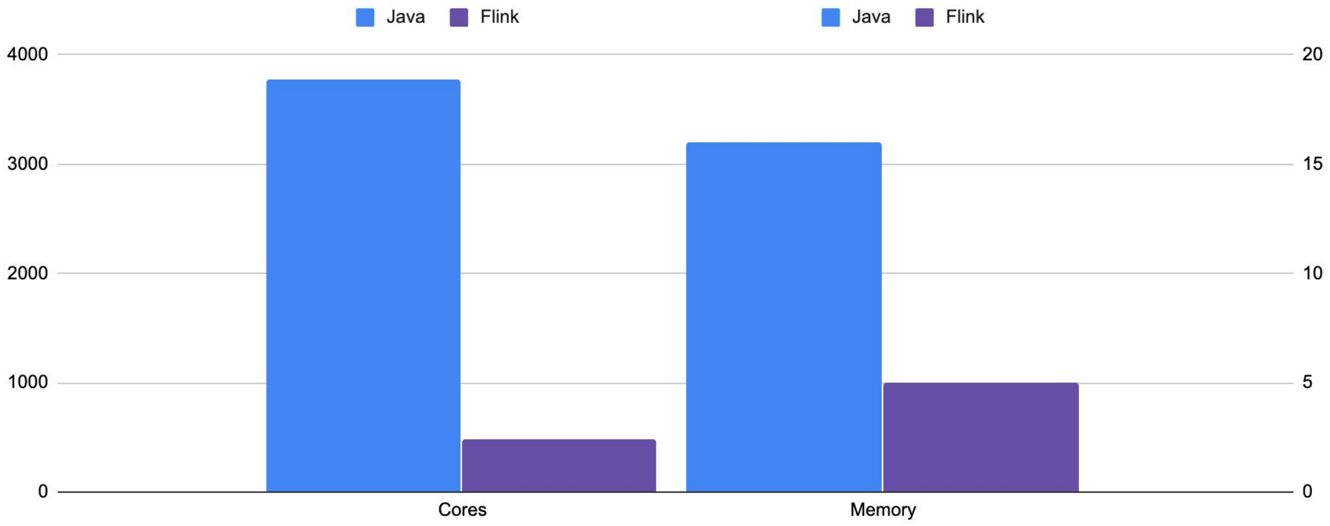
Strong feature set

Operator isolation with keyby lets us use city specific configurations and the Table API offers really nice high level abstractions

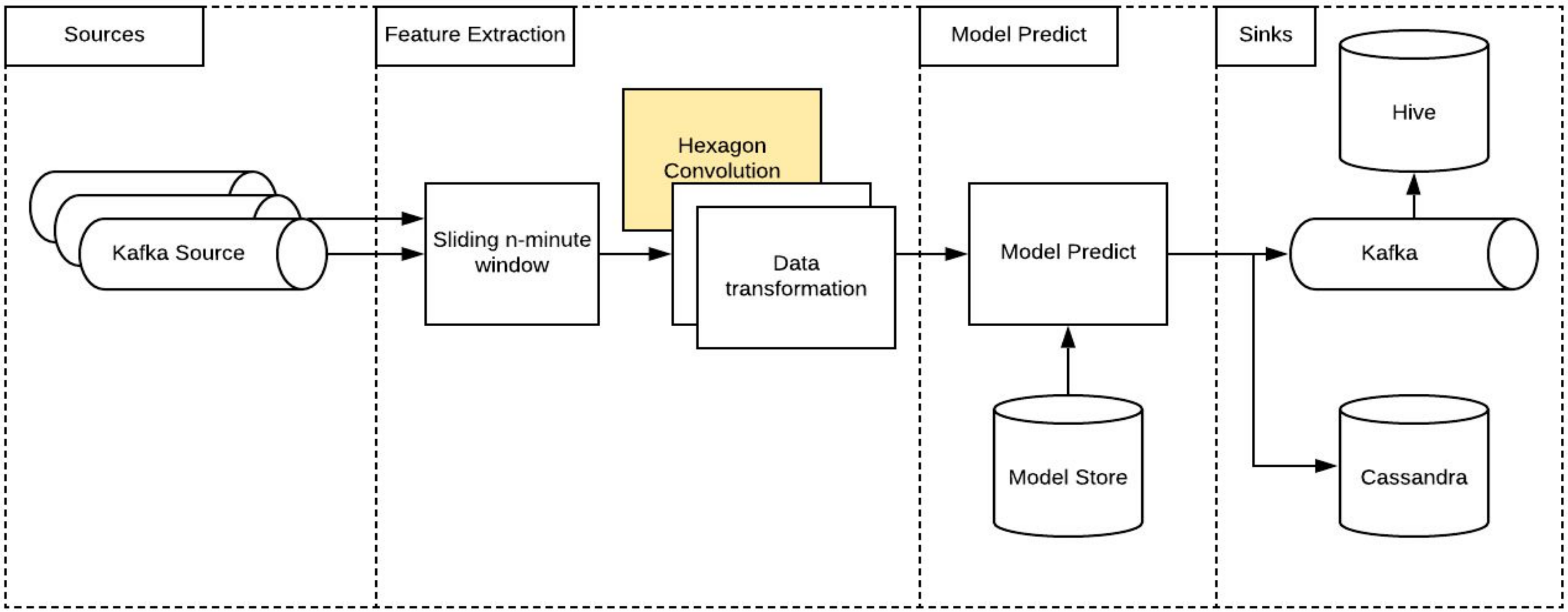
Resource reduction

Significant savings

The combination of both moving our pipelines to Flink and leveraging hexagon convolution has reduced the total required core count by ~90% and memory utilization per box by ~70%



Forecasting Flink Pipeline



Summary

- Uber data is aggregated on hexagons using the [H3 library]
- Geospatial processing is expensive. Leveraging convolution allows for significant performance gains
- Geospatial processing is expensive. Efficient pipeline frameworks are critical with Flink being a very natural fit

Q&A

Additional resources:

- Uber Marketplace
- Uber github