MathWorks

MATLAB CONFERENCE 2018

Scaling up MATLAB Analytics with Kafka and Cloud Services

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Agenda

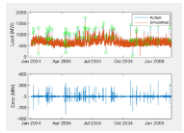
1. Access and Explore Data
2. Preprocess Data
3. Develop Predictive Models
4. Integrate with Production Systems
5. Visualize Results

Files

Databases

Sensors

Working with Messy Data



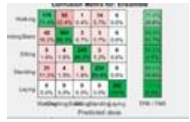
Data Reduction/ Transformation

Feature Extraction

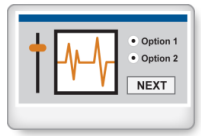
Model Creation e.g. Machine Learning

Parameter Optimization

Model Validation



Desktop Apps



Enterprise Scale Systems

kafka

AWS Kinesis

OSIsoft.

Embedded Devices and Hardware

3rd party dashboards

Spotfire® TIBCO Software

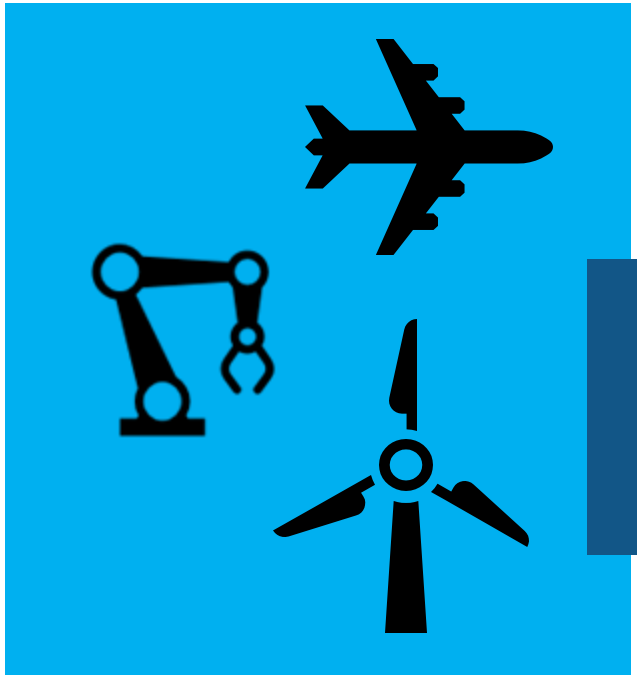
+ableau

Qlik

Power BI

Web apps

The Need for Large-Scale Streaming



Predictive Maintenance

Increase Operational Efficiency

Reduce Unplanned Downtime

Jet engine: ~800TB per day
Turbine: ~ 2 TB per day

More applications require near real-time analytics

Medical Devices

Patient Safety

Better Treatment Outcomes

Connected Cars

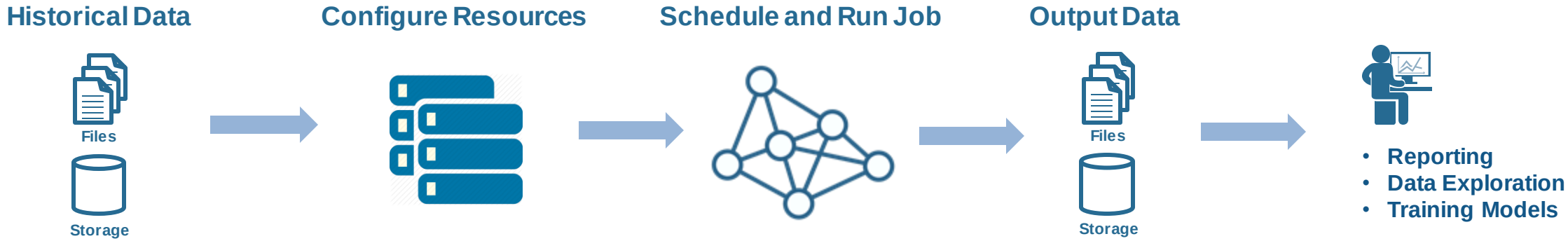
Safety, Maintenance

Advanced Driving Features

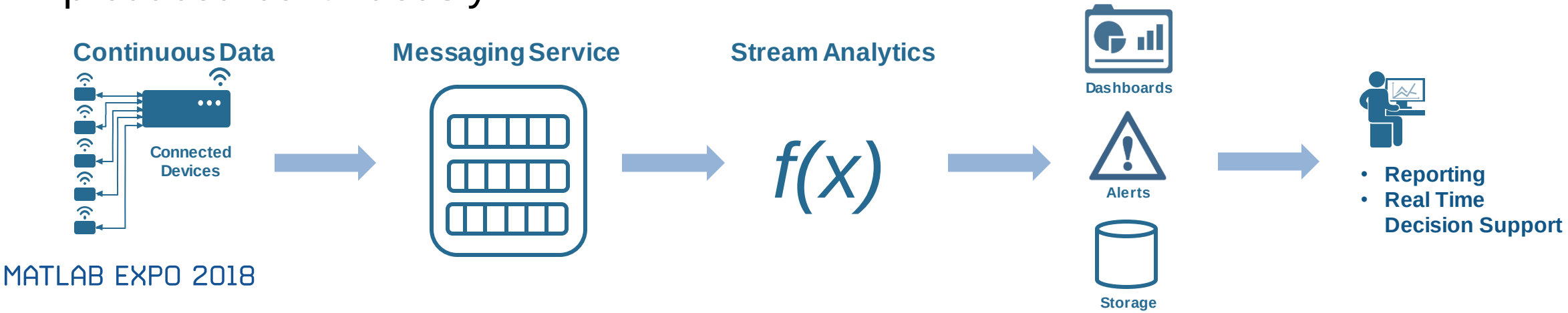
Car: ~25 GB per hour

A quick Intro to Stream Processing

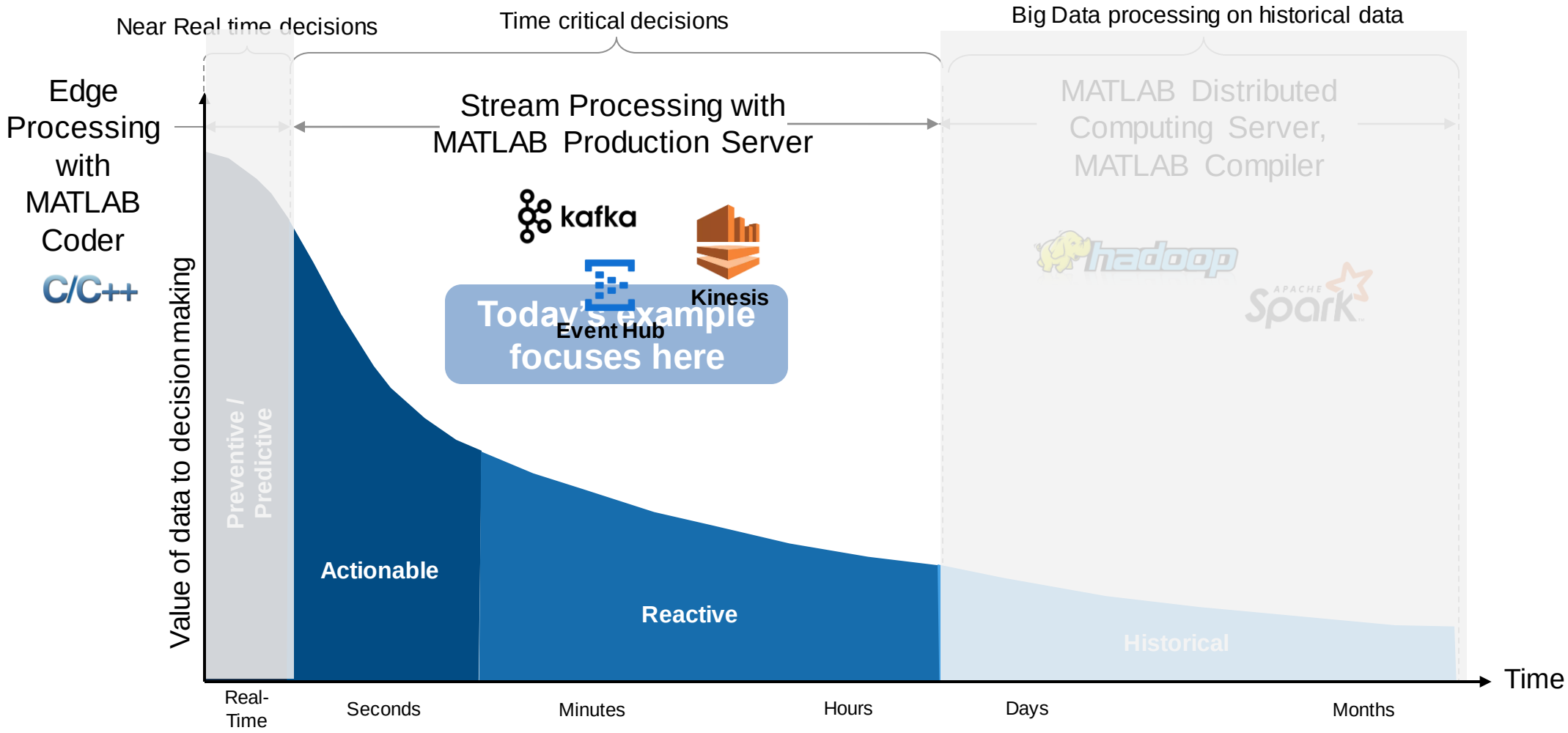
- ***Batch Processing*** applies computation to a finite sized historical data set that was acquired in the past



- ***Stream Processing*** applies computation to an unbounded data set that is produced continuously



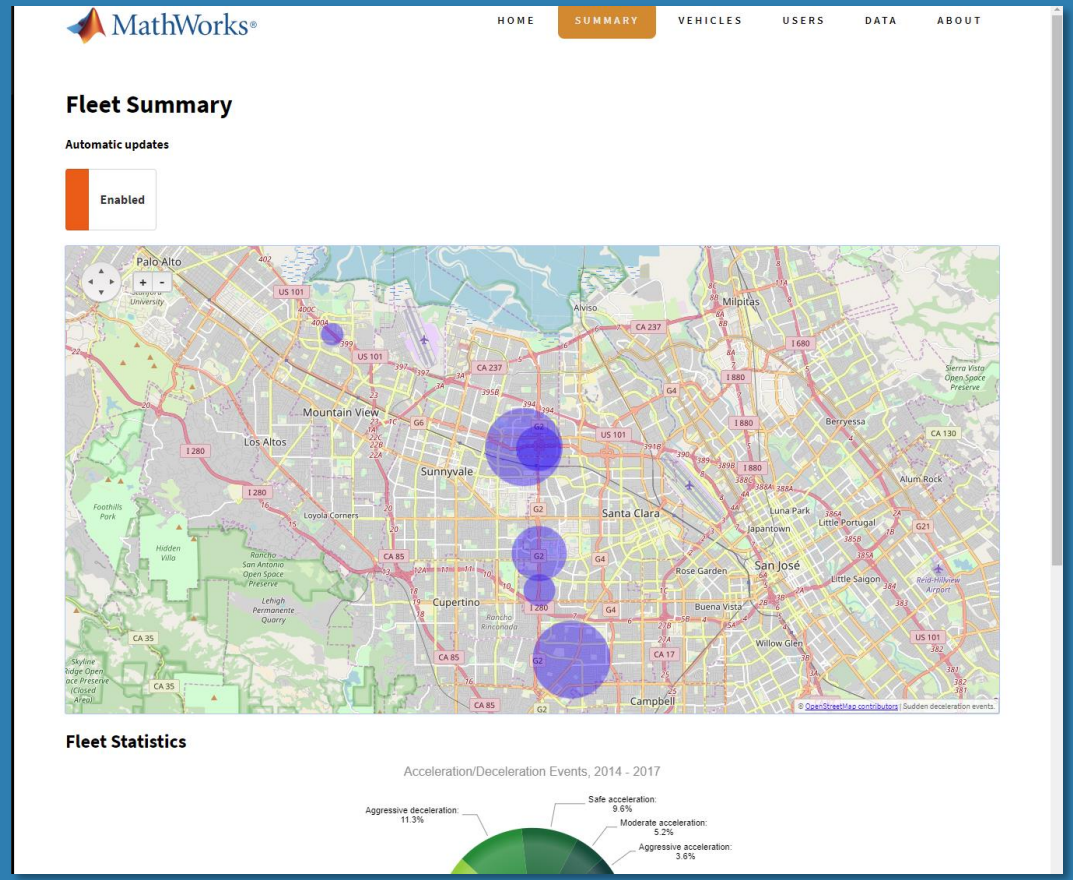
Why stream processing?

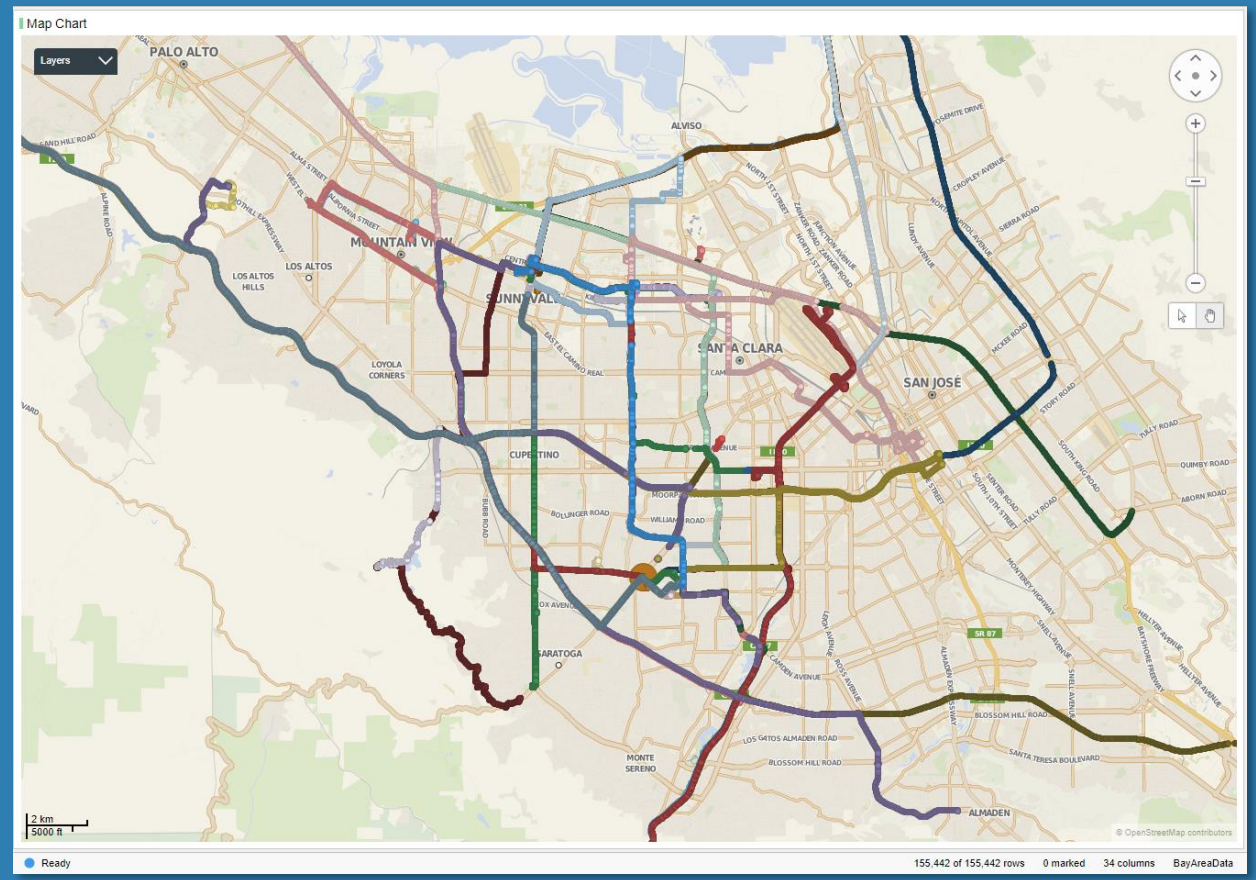


Example Problem – How's my driving?

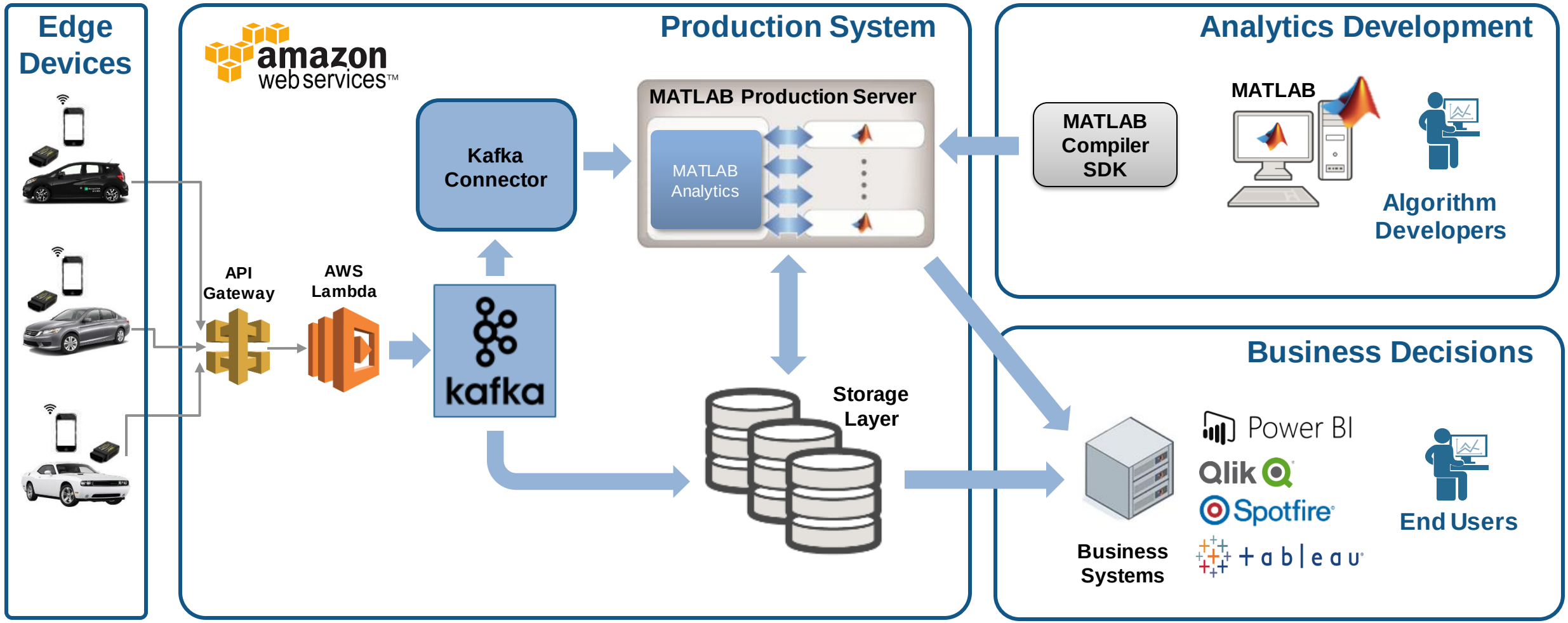
- A group of MathWorks employees installed an OBD dongle in their car that monitors the on-board systems
- Data is streamed to the cloud where it is aggregated and stored
- We would like to use this data to score the driving habits of participants

Example: Fleet Analytics with MATLAB



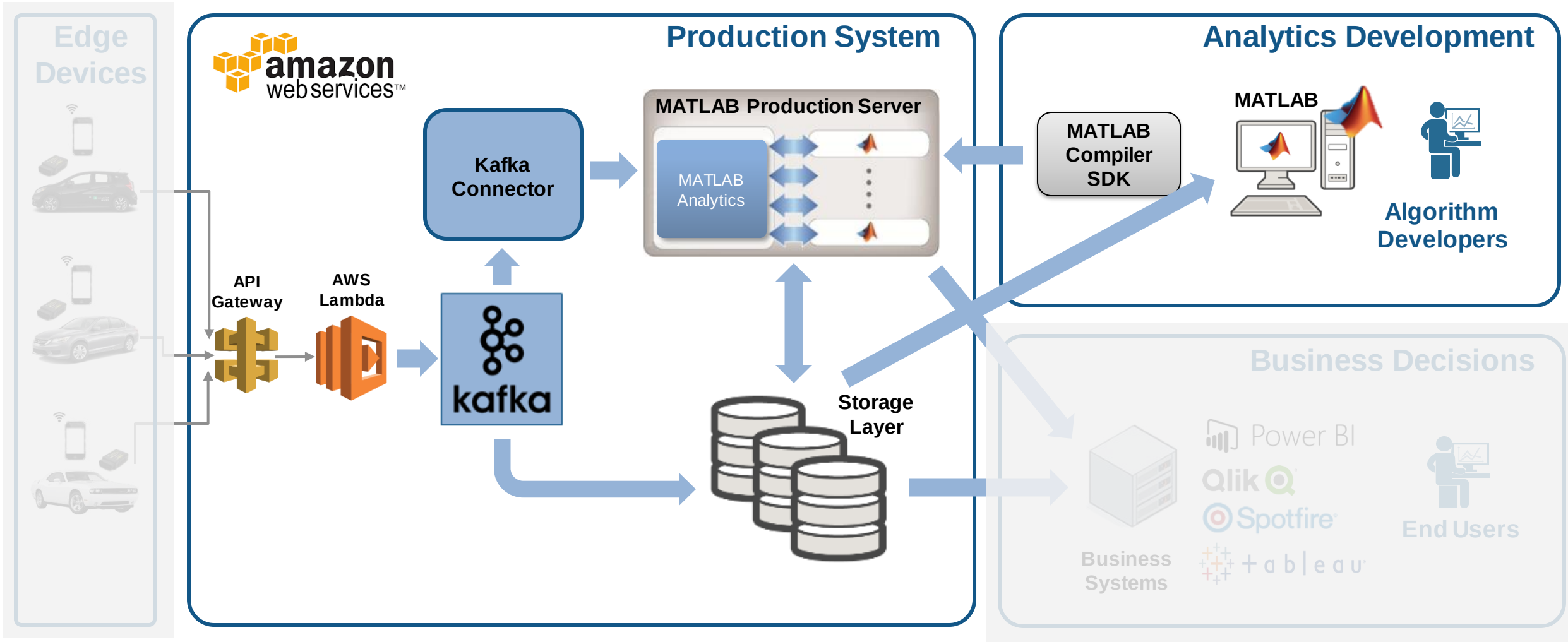


Fleet Analytics Architecture



1 Access and Explore Data

The first step is to clean up the incoming data



The Data: Timestamped messages with JSON encoding

```
{
    "vehicles_id": {"$oid":"55a3fd0069702d5b41000000"},
    "time" : {"$date":"2015-07-13T18:01:35.000Z"},
    "kc" : 1975.0, "kff1225" : 100.65293, "kff125a" : 110.36619, …
}
```

Key

Timestamp

Values

```
{
    "vehicles_id": {"$oid":"55a3fe3569702d5c5c000020"}
    "time":{"$date":"2015-07-13T18:01:53.000Z"},
    "kc" : 2000.0, "kff1225" : 109.65293, "kff125a" : 115.36619,
      …
}
```

```
{
    "vehicles_id": {"$oid":"55a4193569702d115b000001"}
    "time":{"$date":"2015-07-12T19:04:04.000Z"}
    "kc":2200.0, "kff1225" : 112.65293, "kff125a" : 112.36619,
      …
}
```

Access a Sample of Data

Raw Data

	timestamp	1 value	2 key
1	15-Jan-2015 22:12:23	'{ "_id" : { "$oid" : "55a41cb069702d115b059ee0" }, "trip_id" : { "$oid"...	'55a41cb069702d115b059ede'
2	15-Jan-2015 22:12:24	'{ "_id" : { "$oid" : "55a41cb069702d115b059ee1" }, "trip_id" : { "$oid"...	'55a41cb069702d115b059ede'
3	15-Jan-2015 22:12:25	'{ "_id" : { "$oid" : "55a41cb069702d115b059ee2" }, "trip_id" : { "$oid"...	'55a41cb069702d115b059ede'
4	15-Jan-2015 22:12:26	'{ "_id" : { "$oid" : "55a41cb069702d115b059ee3" }, "trip_id" : { "$oid"...	'55a41cb069702d115b059ede'

- ✓ **Decode JSON data**
- ✓ **Create Timetable**

Timetable

t = 4647×40 timetable

	trip_id	VIN	kff1001	kff1005	kff1006	kff1220	kff1221	kff1222	kff1223	kff125a
1 Sun Jul 12 16:18:41 UTC 2015	55a3fe356...	55a3fe356...	17.1000	-84.9323	45.4704	NaN	NaN	NaN	NaN	59.0434
2 Sun Jul 12 16:18:42 UTC 2015	55a3fe356...	55a3fe356...	17.1000	-84.9322	45.4704	NaN	NaN	NaN	NaN	57.8609
3 Sun Jul 12 16:18:43 UTC 2015	55a3fe356...	55a3fe356...	18.9000	-84.9322	45.4705	NaN	NaN	NaN	NaN	52.7147
4 Sun Jul 12 16:18:44 UTC 2015	55a3fe356...	55a3fe356...	18.9000	-84.9322	45.4705	NaN	NaN	NaN	NaN	51.1983
5 Sun Jul 12 16:18:45 UTC 2015	55a3fe356...	55a3fe356...	18.0000	-84.9321	45.4706	NaN	NaN	NaN	NaN	49.1095
6 Sun Jul 12 16:19:13 UTC 2015	55a3fe356...	55a3fe356...	58.5000	-84.9305	45.4686	NaN	NaN	NaN	NaN	73.2005
7 Sun Jul 12 16:19:14 UTC 2015	55a3fe356...	55a3fe356...	56.7000	-84.9304	45.4685	NaN	NaN	NaN	NaN	75.3612
8 Sun Jul 12 16:19:15 UTC 2015	55a3fe356...	55a3fe356...	57.6000	-84.9304	45.4683	NaN	NaN	NaN	NaN	70.7542
9 Sun Jul 12 16:19:16 UTC 2015	55a3fe356...	55a3fe356...	56.7000	-84.9303	45.4682	NaN	NaN	NaN	NaN	62.8340

Develop a Preprocessing Function

Timetable

t = 4647×40 timetable

	trip_id	VIN	kff1001	kff1005	kff1006	kff1220	kff1221	kff1222	kff1223	kff125a
1 Sun Jul 12 16:18:41 UTC 2015	55a3fe356...	55a3fe356...	17.1000	-84.9323	45.4704	NaN	NaN	NaN	NaN	59.0434
2 Sun Jul 12 16:18:42 UTC 2015	55a3fe356...	55a3fe356...	17.1000	-84.9322	45.4704	NaN	NaN	NaN	NaN	57.8609
3 Sun Jul 12 16:18:43 UTC 2015	55a3fe356...	55a3fe356...	18.9000	-84.9322	45.4705	NaN	NaN	NaN	NaN	52.7147
4 Sun Jul 12 16:18:44 UTC 2015	55a3fe356...	55a3fe356...	18.9000	-84.9322	45.4705	NaN	NaN	NaN	NaN	51.1983
5 Sun Jul 12 16:18:45 UTC 2015	55a3fe356...	55a3fe356...	18.0000	-84.9321	45.4706	NaN	NaN	NaN	NaN	49.1095
6 Sun Jul 12 16:19:13 UTC 2015	55a3fe356...	55a3fe356...	58.5000	-84.9305	45.468	NaN	NaN	NaN	NaN	73.2006
7 Sun Jul 12 16:19:14 UTC 2015	55a3fe356...	55a3fe356...	56.7000	-84.9304	45.468					
8 Sun Jul 12 16:19:15 UTC 2015	55a3fe356...	55a3fe356...	57.6000	-84.9304	45.468					
9 Sun Jul 12 16:19:16 UTC 2015	55a3fe356...	55a3fe356...	56.7000	-84.9303	45.468					

- ✓ Clean up
- ✓ Enrich
- ✓ Restructure

Preprocess data

```
t = sortrows(t);
t = rmmissing(t,'MinNumMissing',width(t)-2);
```

Perform windowed calculations

```
t.Speed = movmedian(t.SpeedGPS,3);
t.D1 = [0;diff(t.SpeedGPS)];
```

```
[tmin,tmax] = bounds(t.time);
tnew = tmin:seconds(10):tmax;
countsByTime = retime(t(:,'Event'),tnew,@histcounts);
```

Ad Hoc Access to Data from MATLAB

athenaQuery.mlx

Access the data in S3

Bring up the AthenaClient

```
athenaClient = aws.athena.Client();
athenaClient.Database = 'trainingdata';
athenaClient.initialize();
```

Create a query and submit

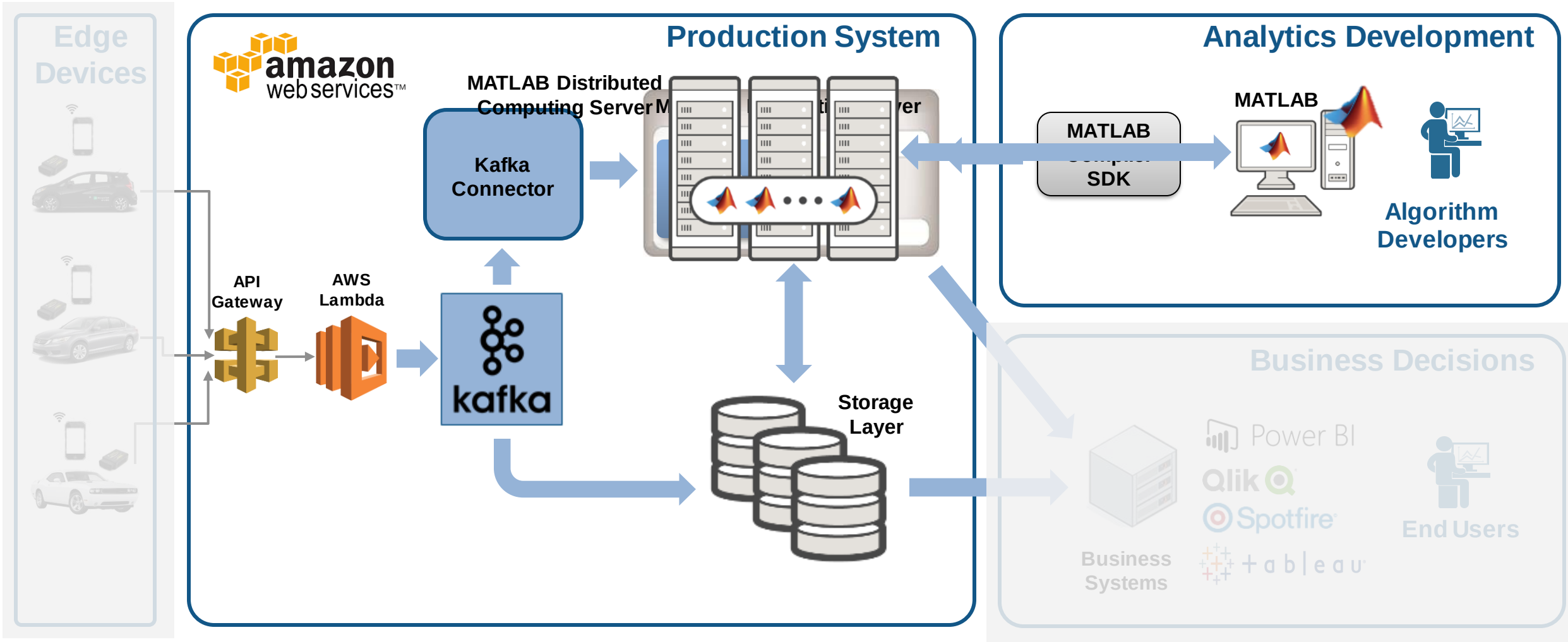
```
athenaClient.submitQuery('SELECT * FROM "trainingdata"."sampledata" limit 100','s3://fleettrainingdata')
```

Fetch data as a table for easy analysis

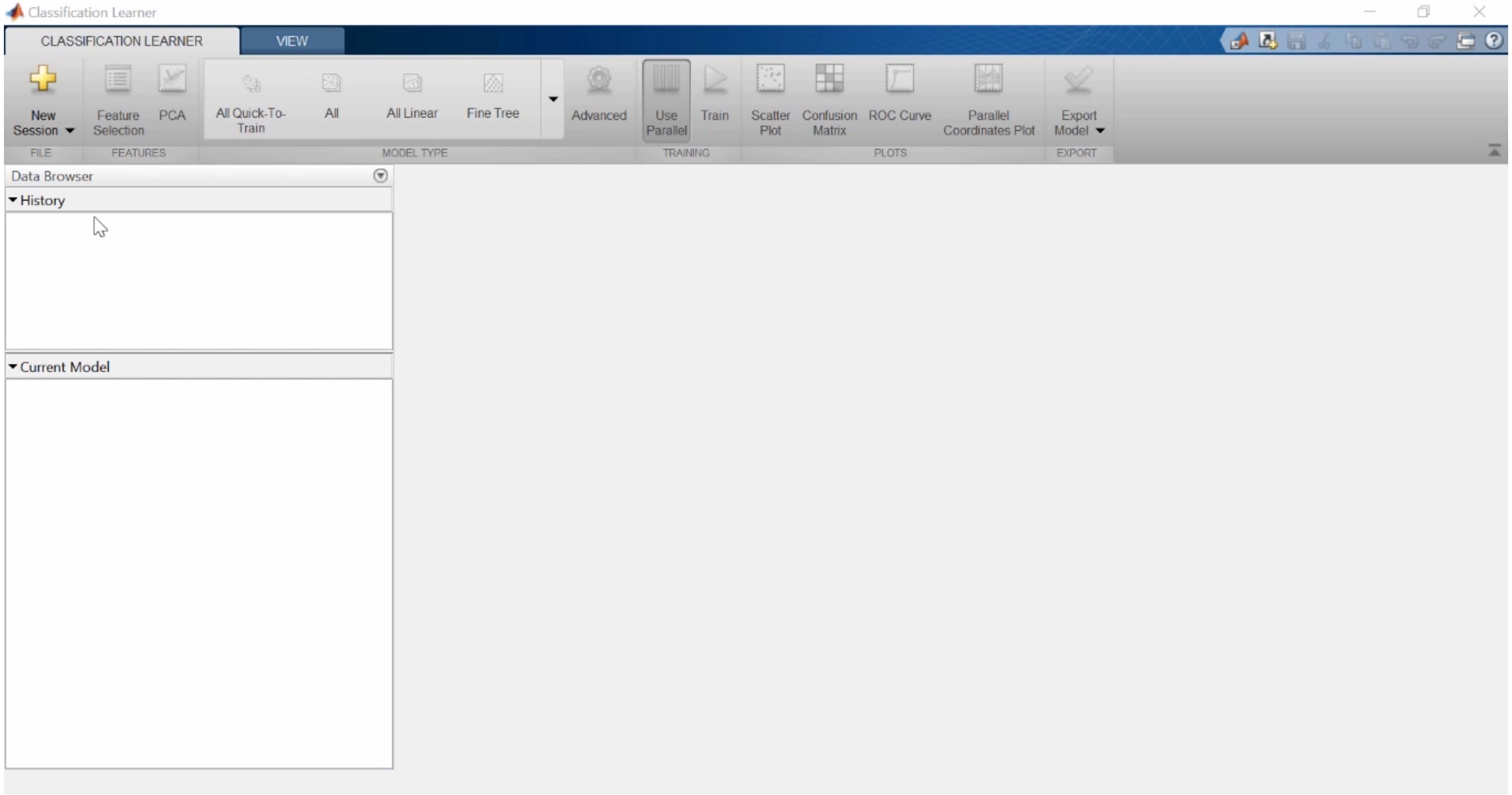
```
ds = datastore('s3://fleettrainingdata/*.csv');
ds.NumHeaderLines = 2;
data = table(ds);
```

Your usual MATLAB workflow goes here

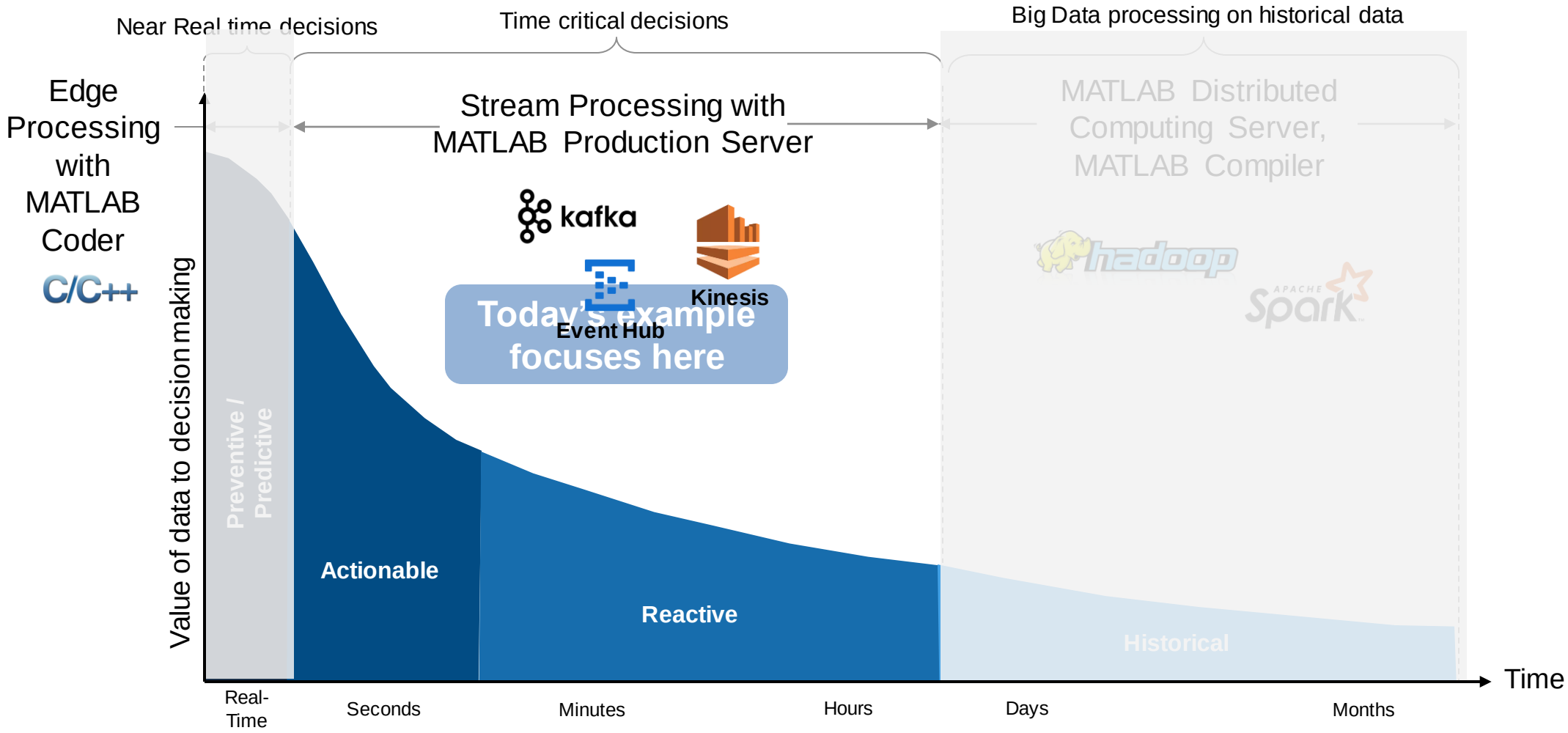
Develop a Predictive Model



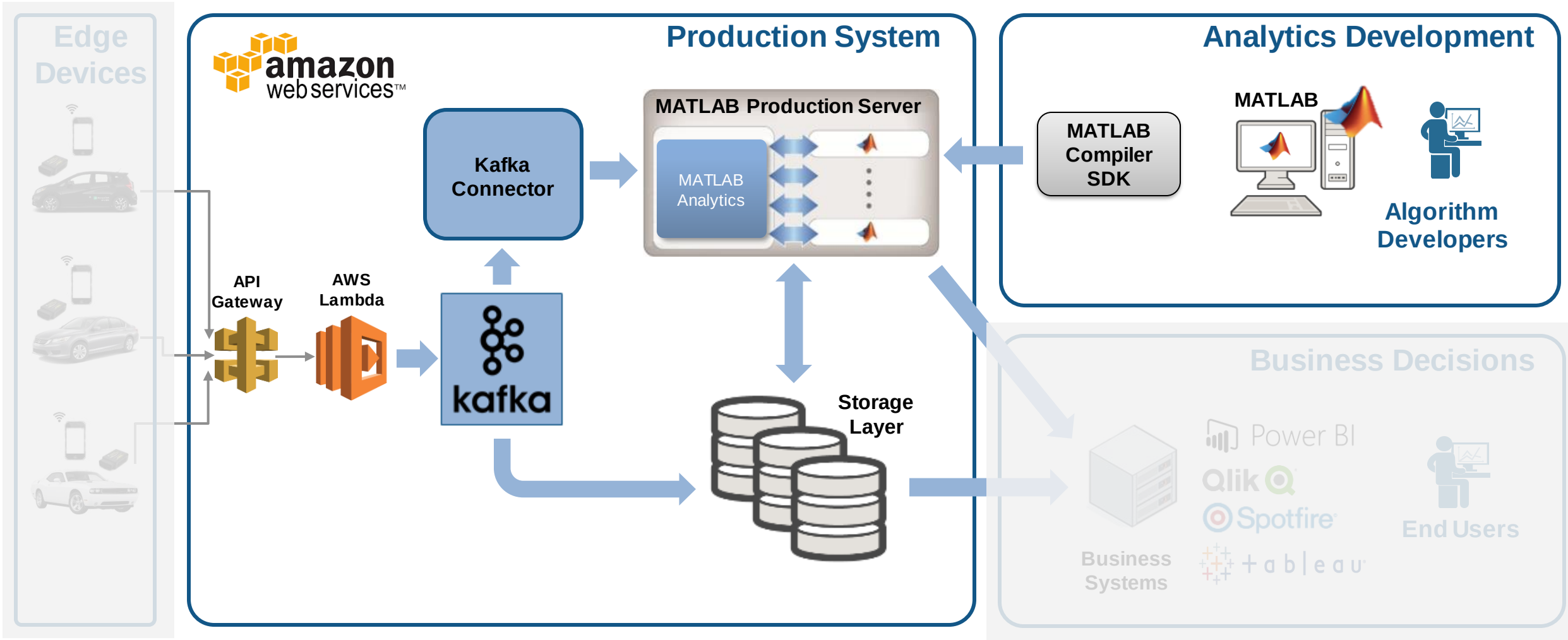
Develop a Predictive Model in MATLAB



Why stream processing?



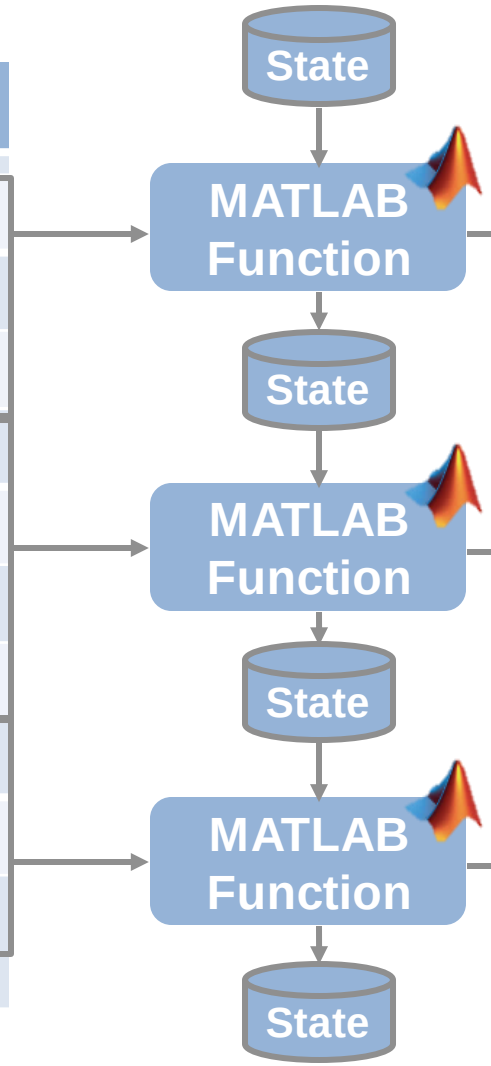
Integrate Analytics with Production Systems



Streaming data is treated as an unbounded Timetable

Input Table

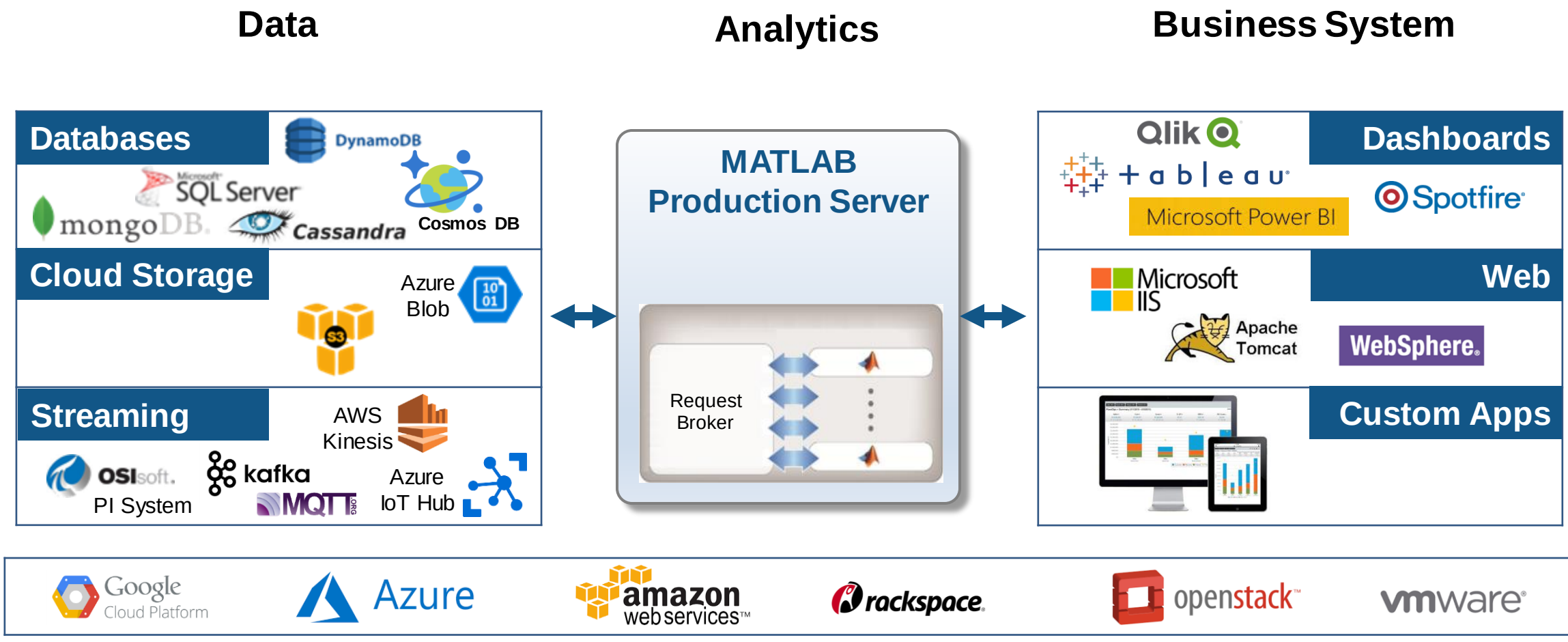
Event Time	Vehicle	RPM	Torque	Fuel Flow
18:01:10	55a3fd	1975	100	110
18:10:30	55a3fe	2000	109	115
18:05:20	55a3fd	1980	105	105
18:10:45	55a3fd	2100	110	100
18:30:10	55a419	2000	100	110
18:35:20	55a419	1960	103	105
18:20:40	55a3fe	1970	112	104
18:39:30	55a419	2100	105	110
18:30:00	55a3fe	1980	110	113
18:30:50	55a3fe	2000	100	110
…	…	…	…	…



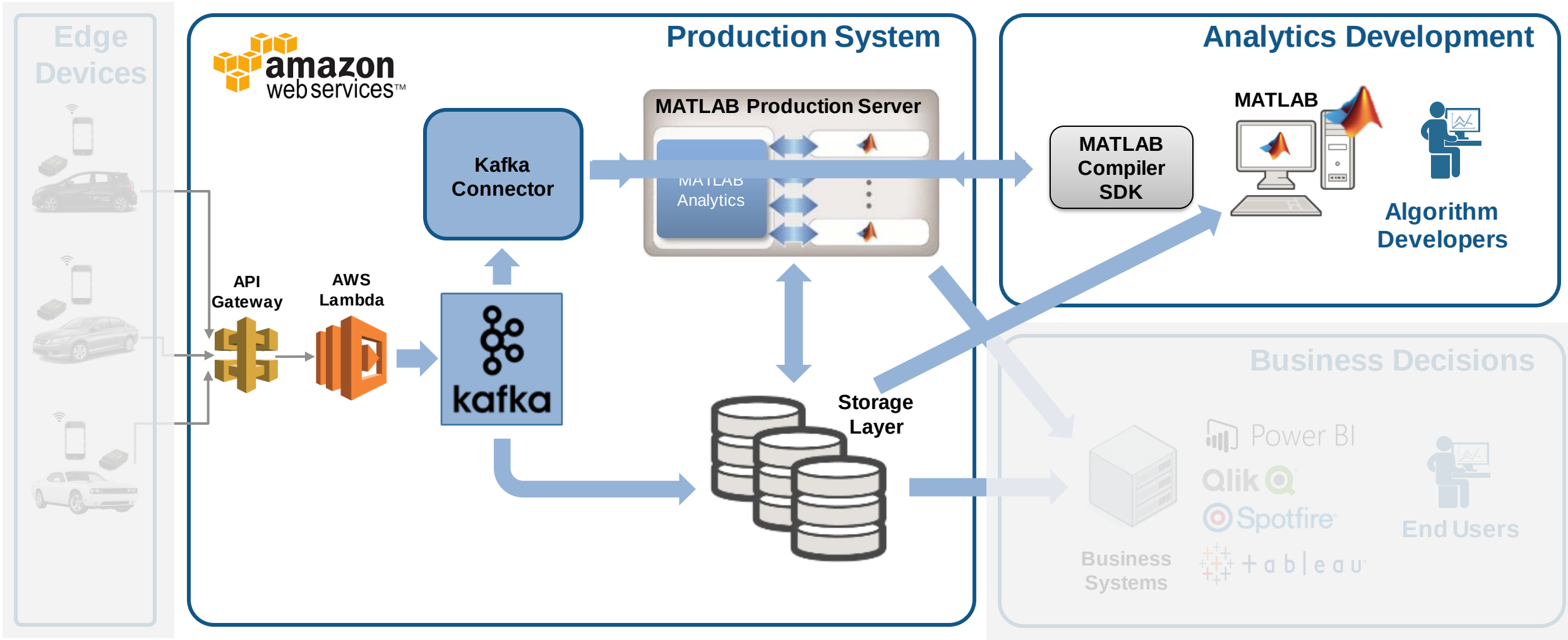
Output Table

Time window		Vehicle	Score
…		…	…
18:00:00	18:10:00	55a3fd	5
		55a3fe	…
		55a419	…
18:10:00	18:20:00	55a3fd	7
		55a3fe	3
		55a419	…
18:20:00	18:30:00	55a3fd	…
		55a3fe	4
		55a419	…
18:30:00	18:40:00	55a3fd	…
		55a3fe	5
		55a419	8

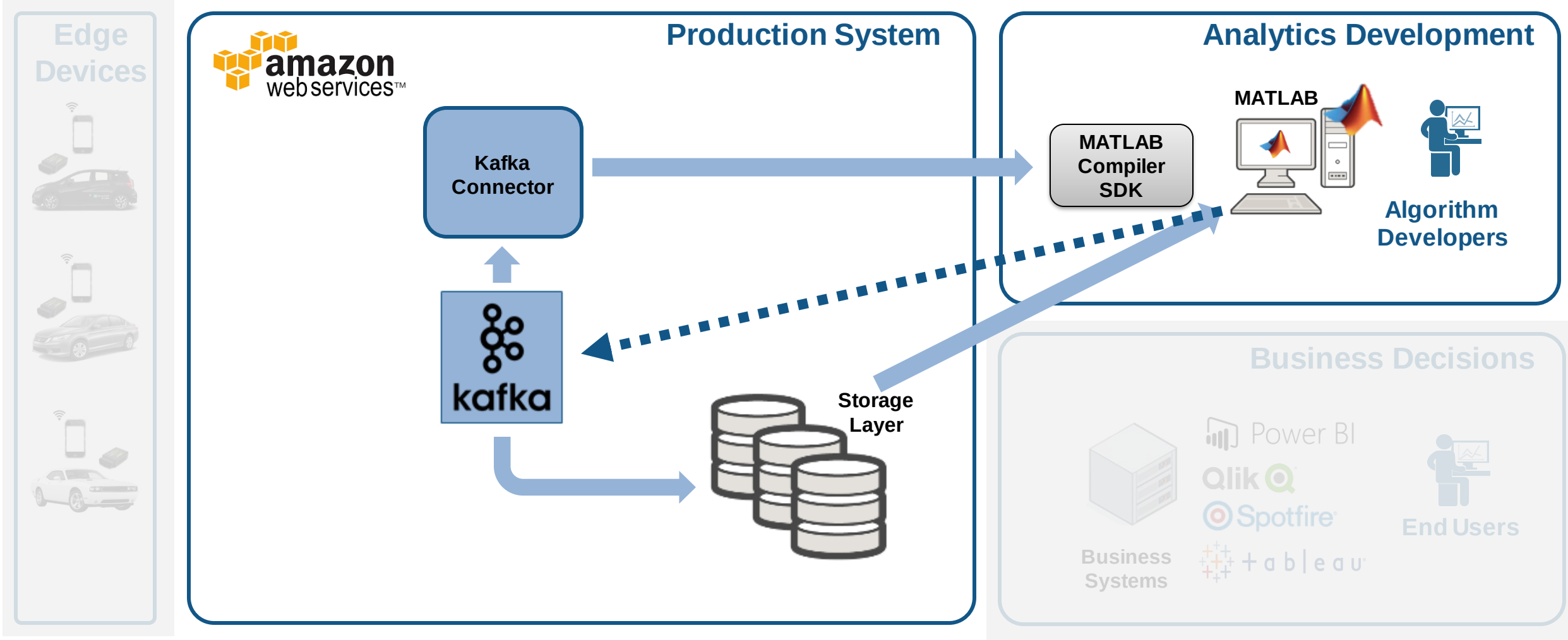
Introducing MATLAB Production Server



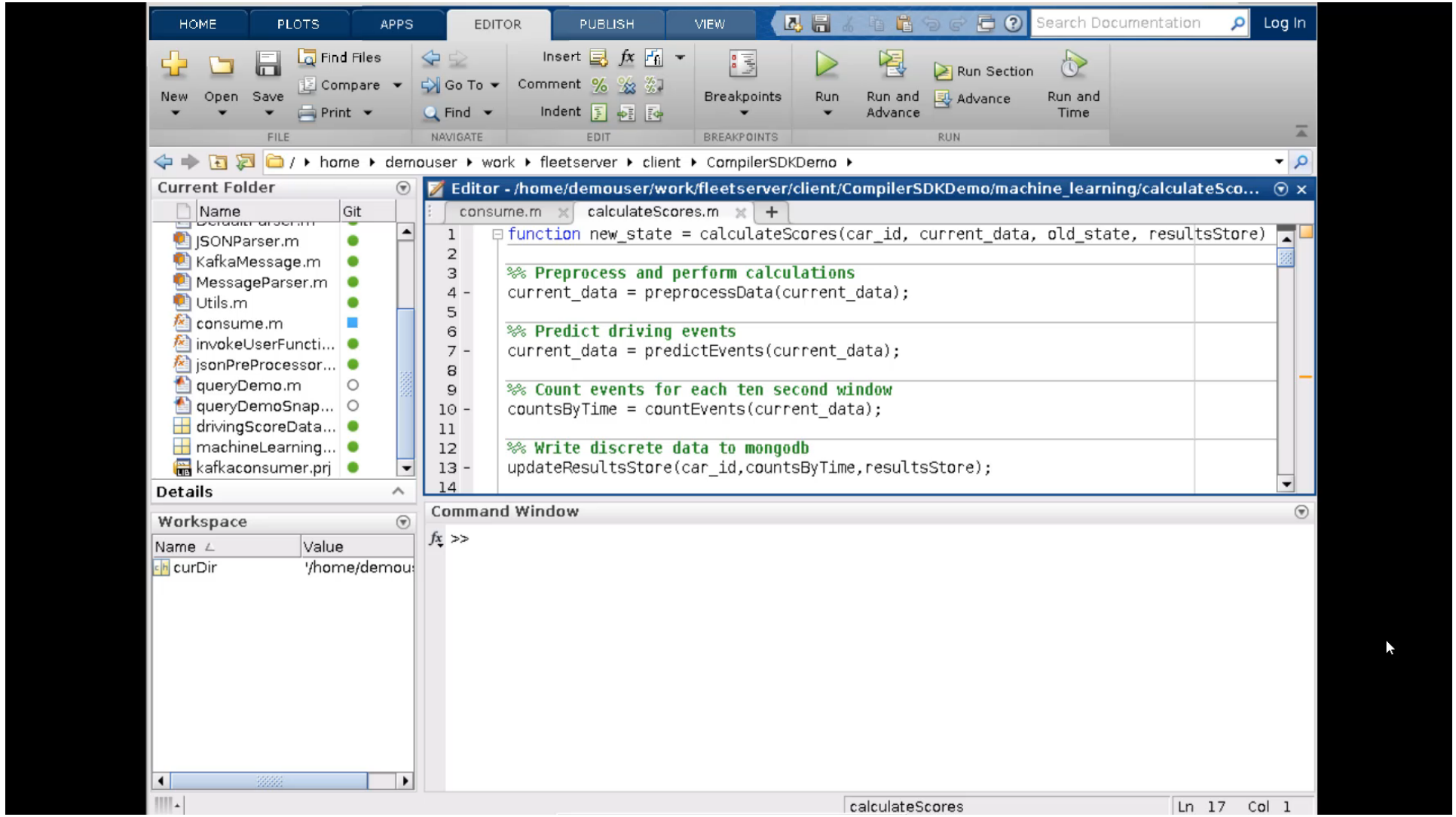
Develop and Deploy a Stream Processing Function



Debug a Stream Processing Function in MATLAB

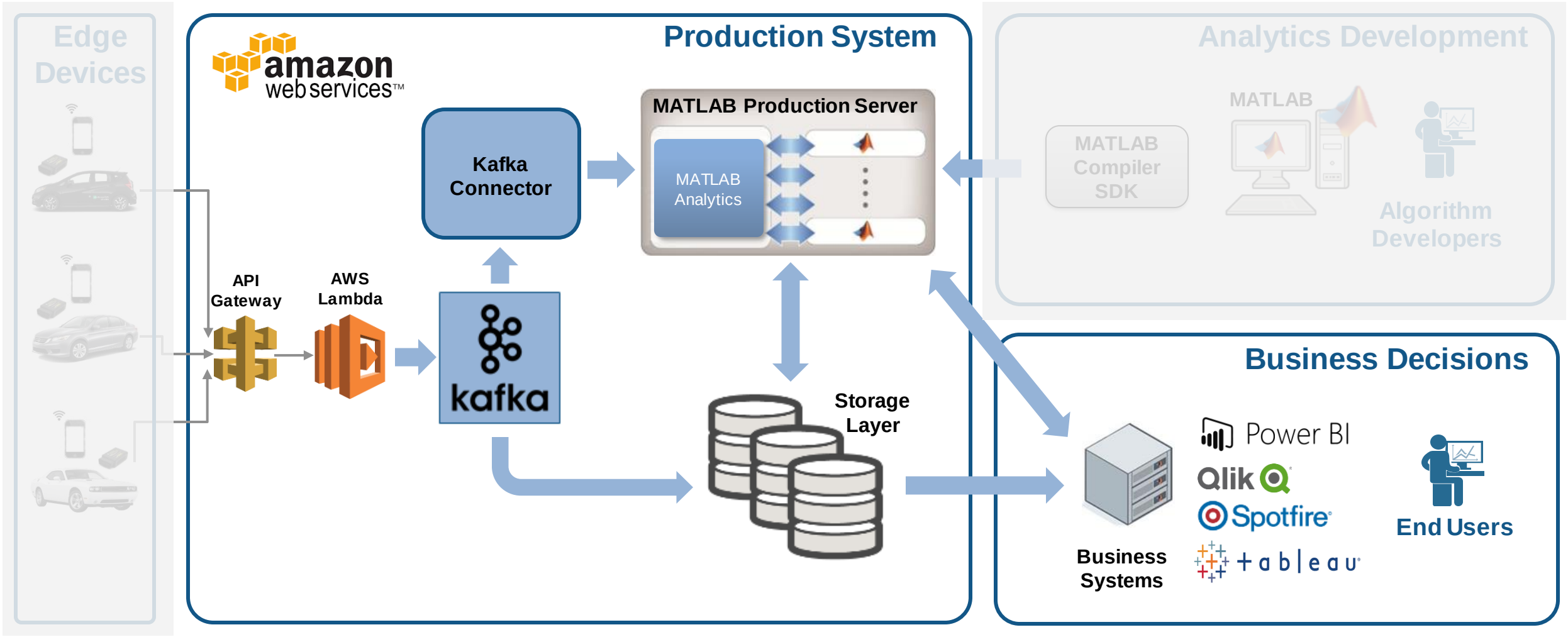


Debug a Stream Processing Function in MATLAB

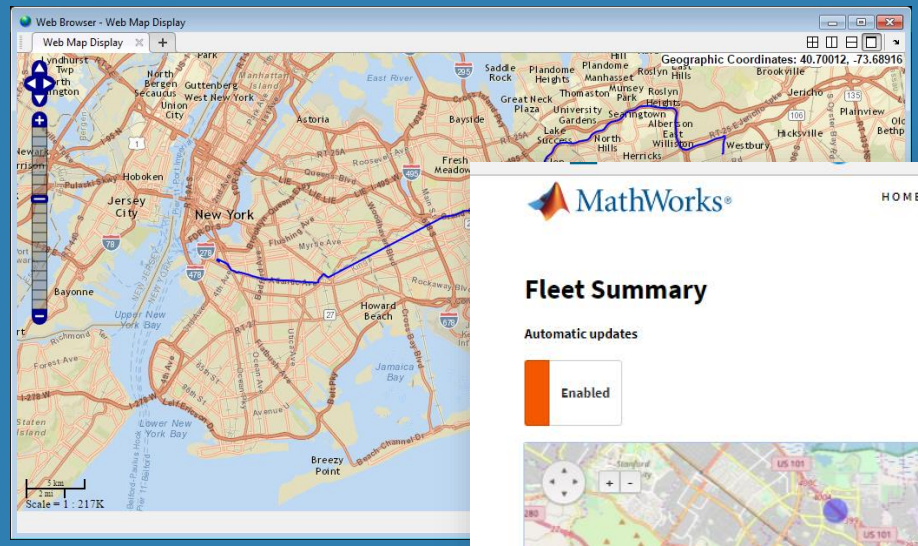


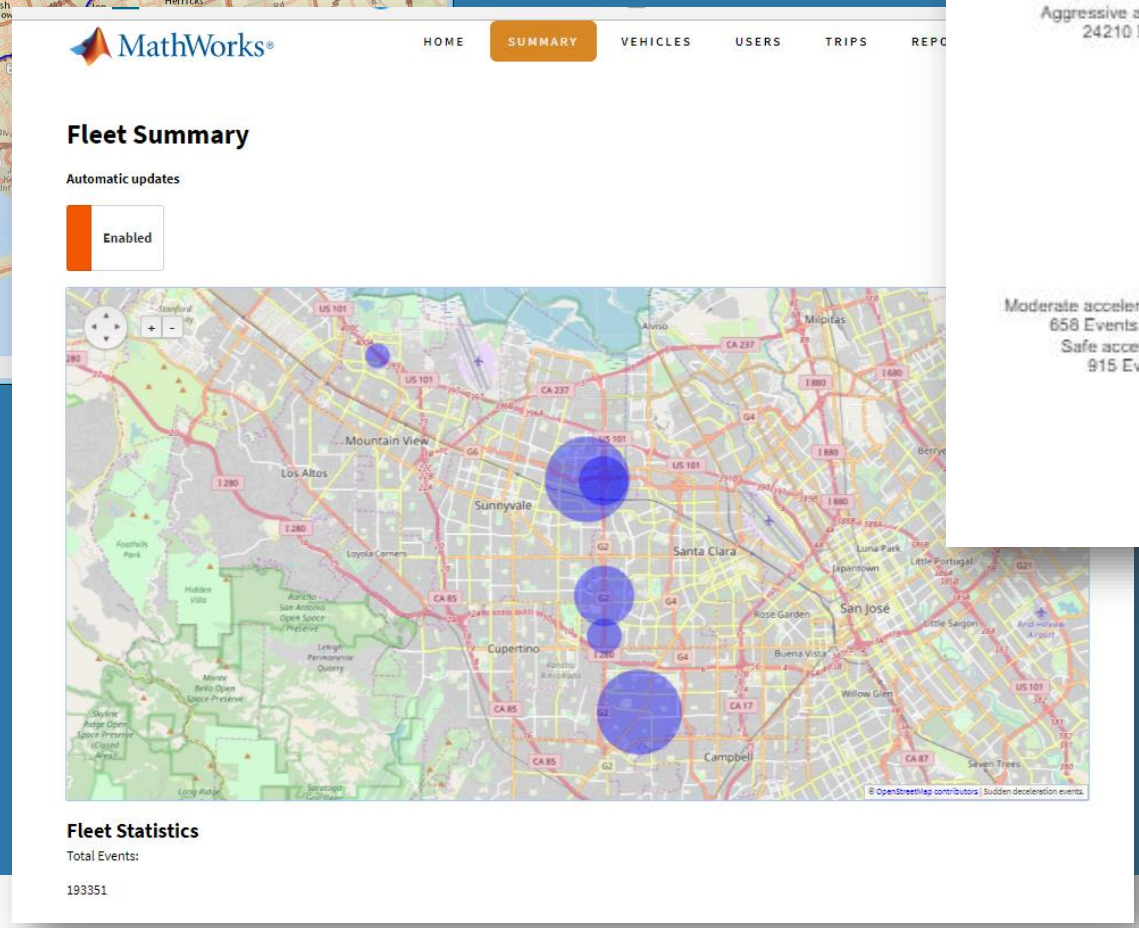
4 Integrate with Production Systems

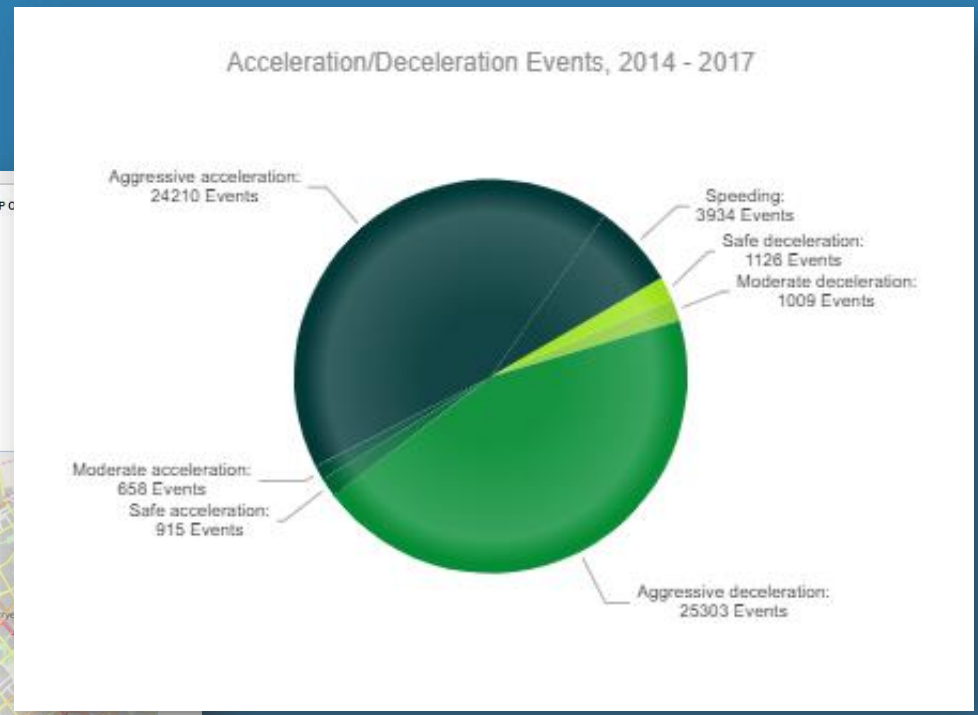
Tie in your Dashboard Application



Complete Your Application

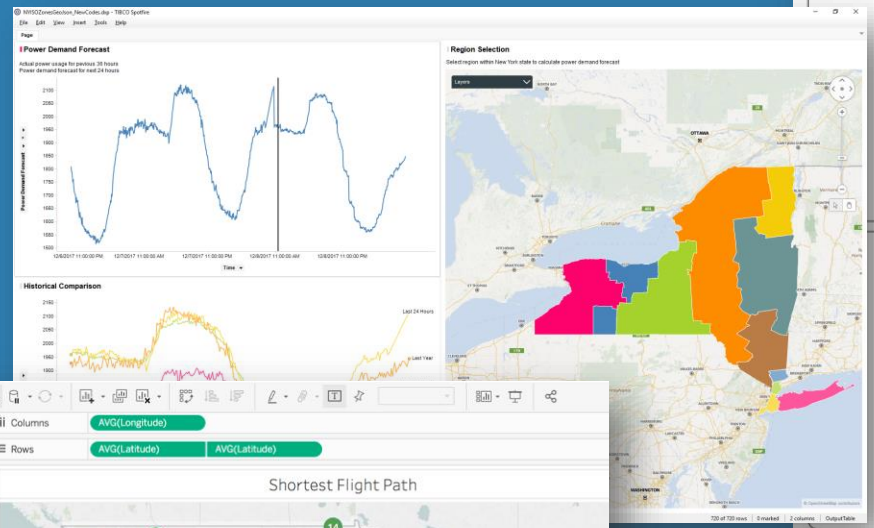




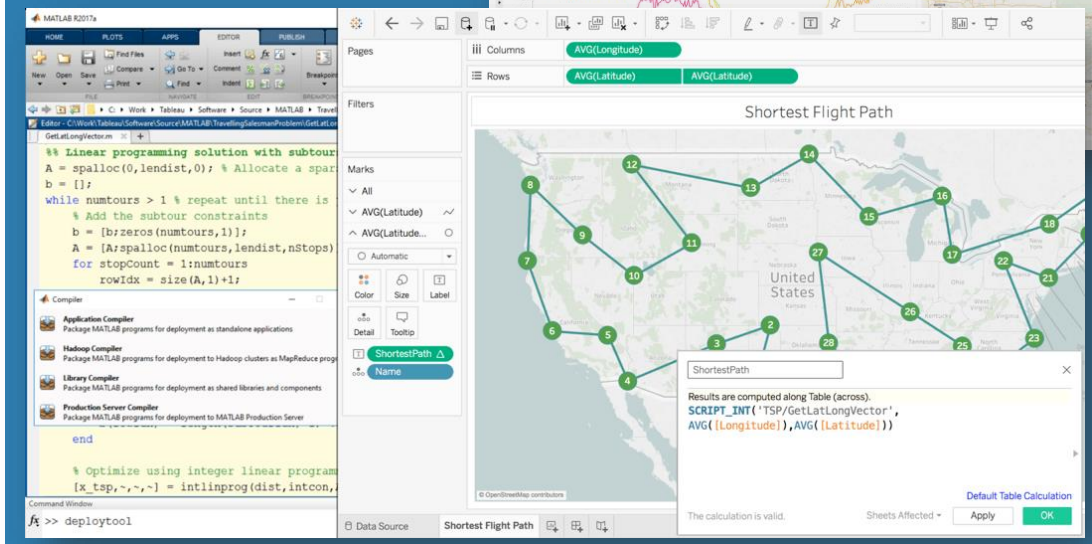


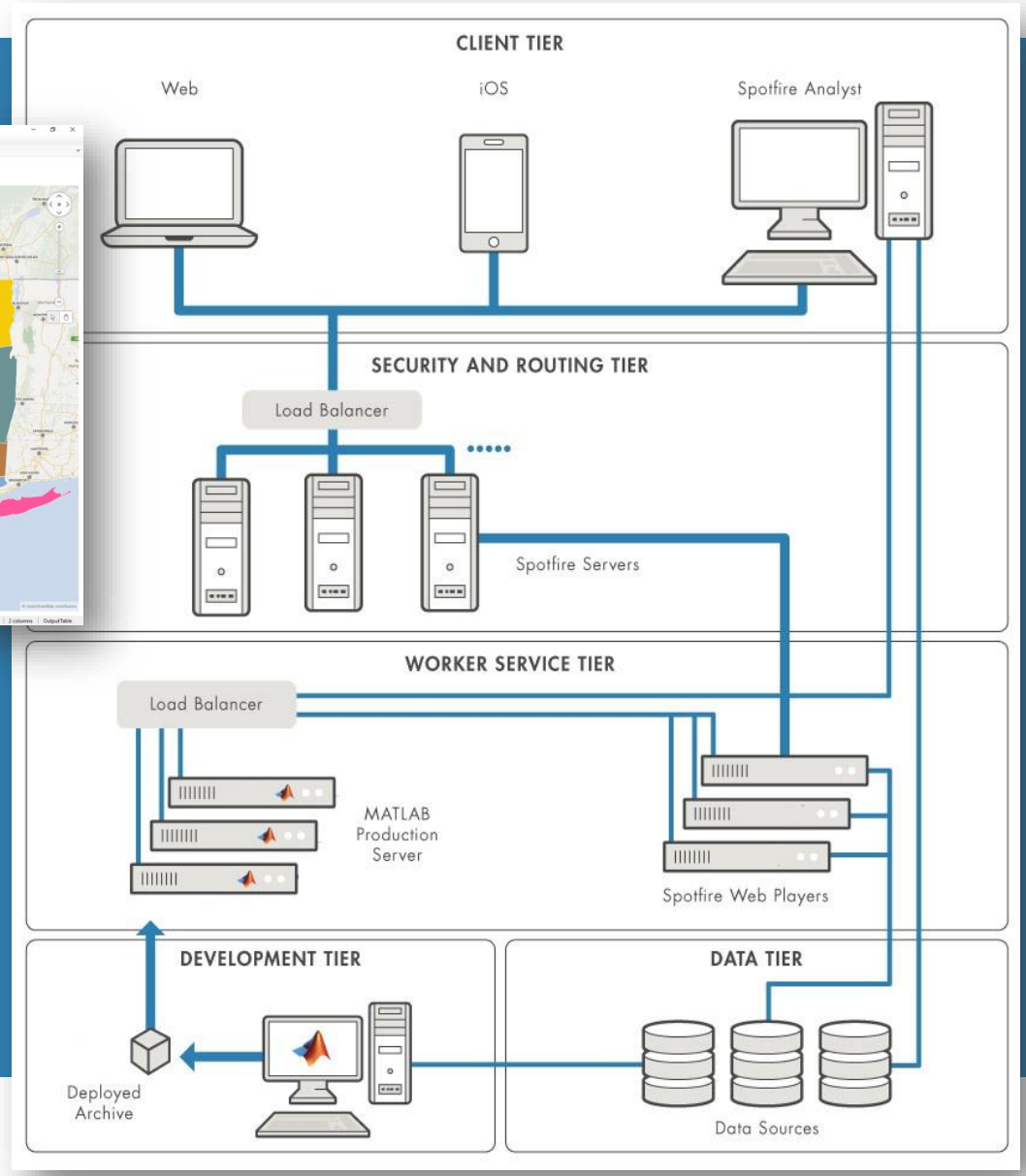
Scalable Analytics with Enterprise BI Tools

TIBCO Spotfire



Tableau





Key Takeaways

- MATLAB connects directly to your data so you can quickly design and validate algorithms
- The MATLAB language and apps enable fast design iterations
- MATLAB Production Server enables easy integration of your MATLAB algorithms with enterprise production systems
- You to spend your time understanding the data and designing algorithms

Resources to learn and get started

- Data Analytics with MATLAB
- MATLAB Production Server
- MATLAB Compiler SDK
- Statistics and Machine Learning Toolbox
- Database Toolbox
- Mapping Toolbox
- MATLAB with TIBCO Spotfire
- MATLAB with Tableau
- MATLAB with MongoDB