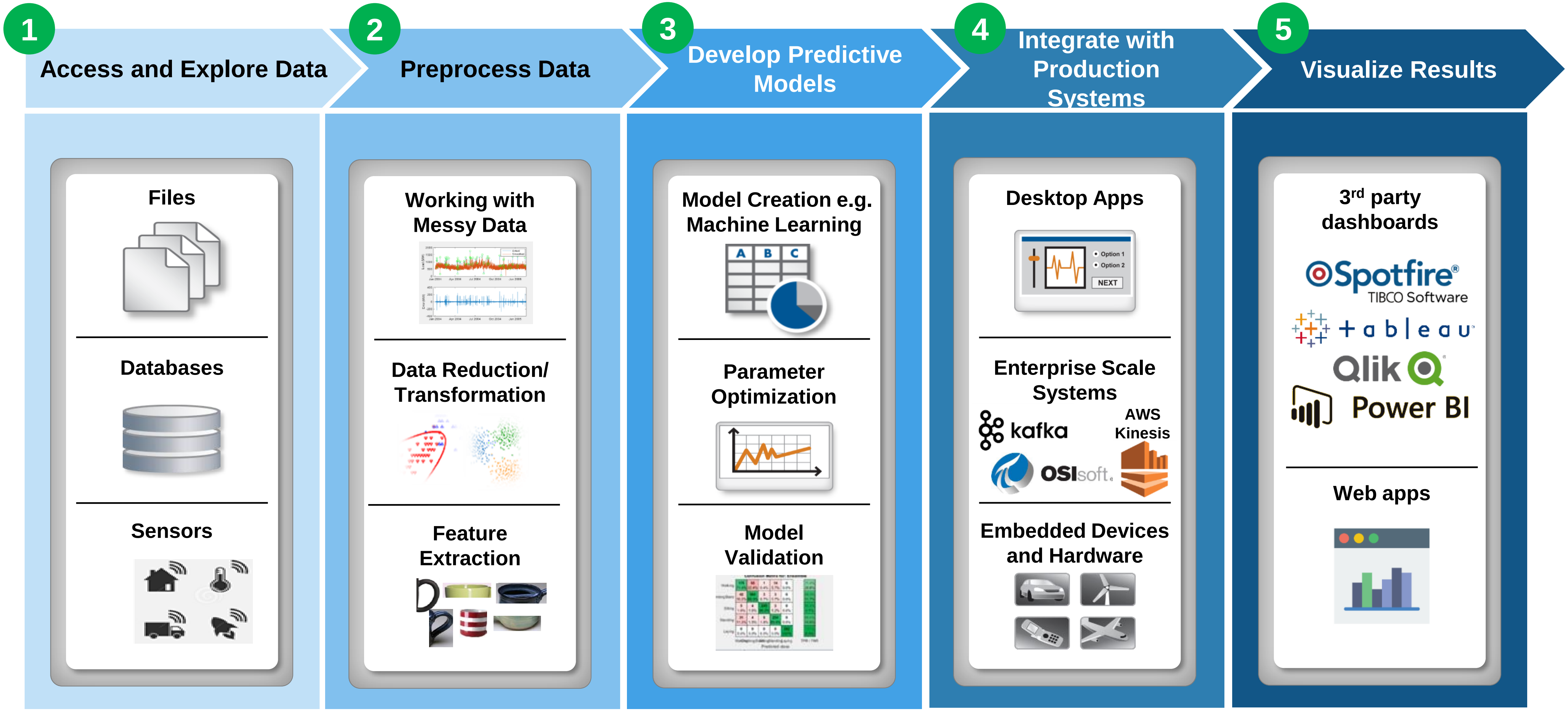
MATLAB EXPO 2018

Scaling up MATLAB Analytics with Kafka and Cloud Services

Christoph Stockhammer

Agenda



1 Access and Explore Data

- Files
- Databases
- Sensors

2 Preprocess Data

- Working with Messy Data
- Data Reduction/ Transformation
- Feature Extraction

3 Develop Predictive Models

- Model Creation e.g. Machine Learning
- Parameter Optimization
- Model Validation

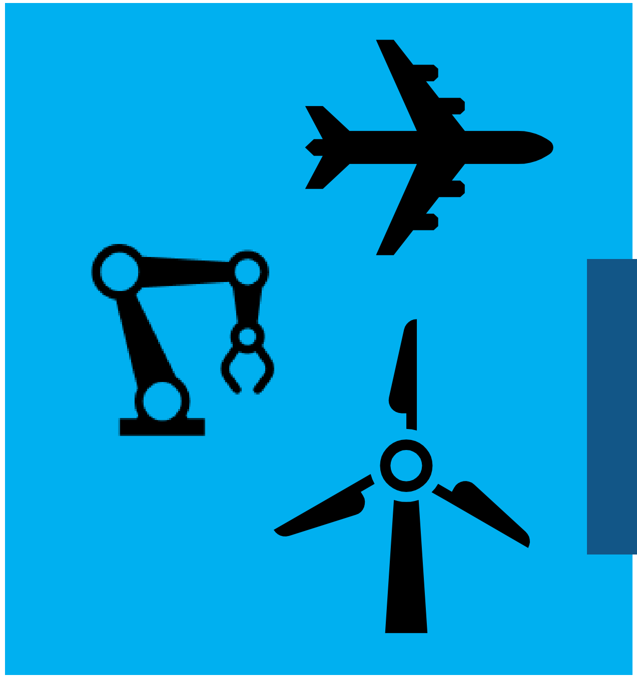
4 Integrate with Production Systems

- Desktop Apps
- Enterprise Scale Systems
- Embedded Devices and Hardware

5 Visualize Results

- 3rd party dashboards
- Web apps

The Need for Large-Scale Streaming



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

Predictive Maintenance

Increase Operational Efficiency

Reduce Unplanned Downtime

More applications require near real-time analytics

Medical Devices

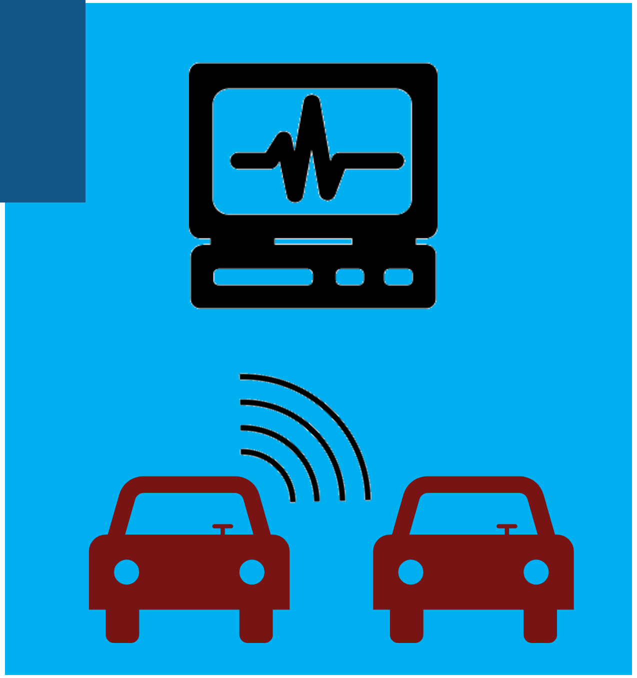
Patient Safety

Better Treatment Outcomes

Connected Cars

Safety, Maintenance

Advanced Driving Features

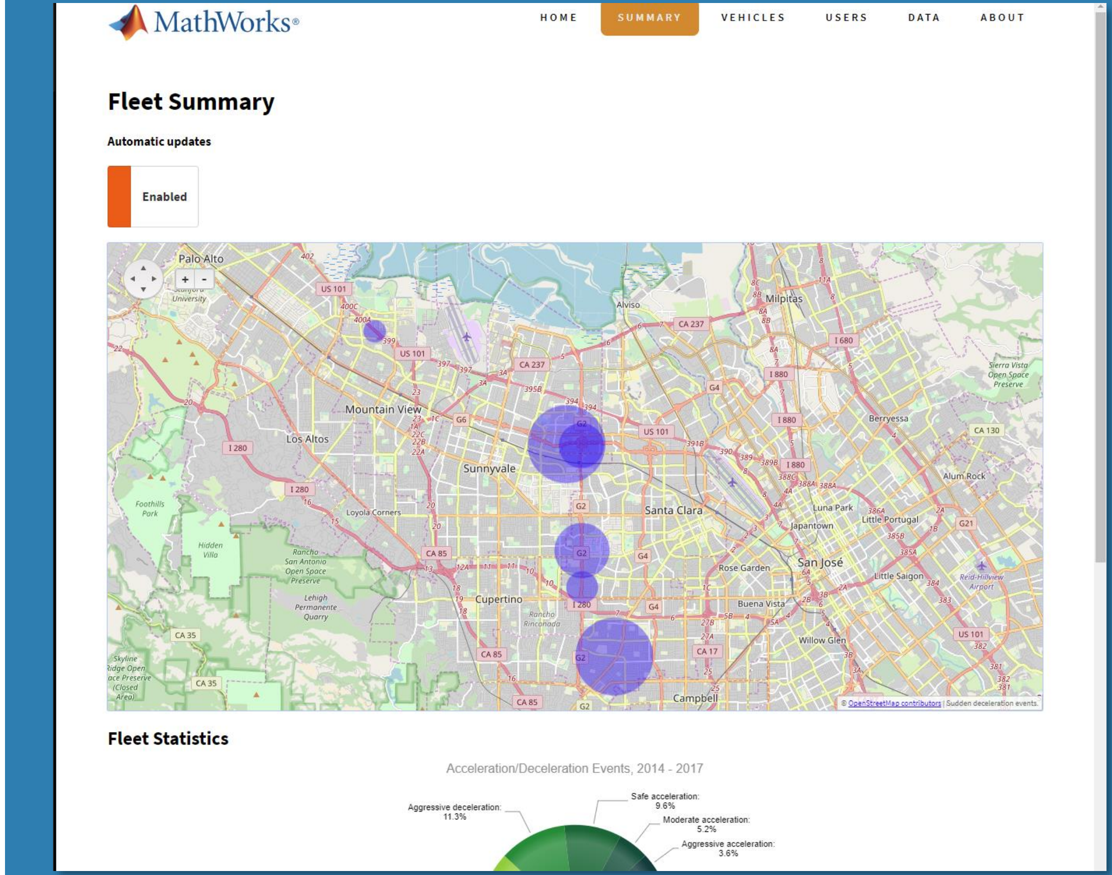


Car: ~25 GB per hour

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 Summary

Automatic updates

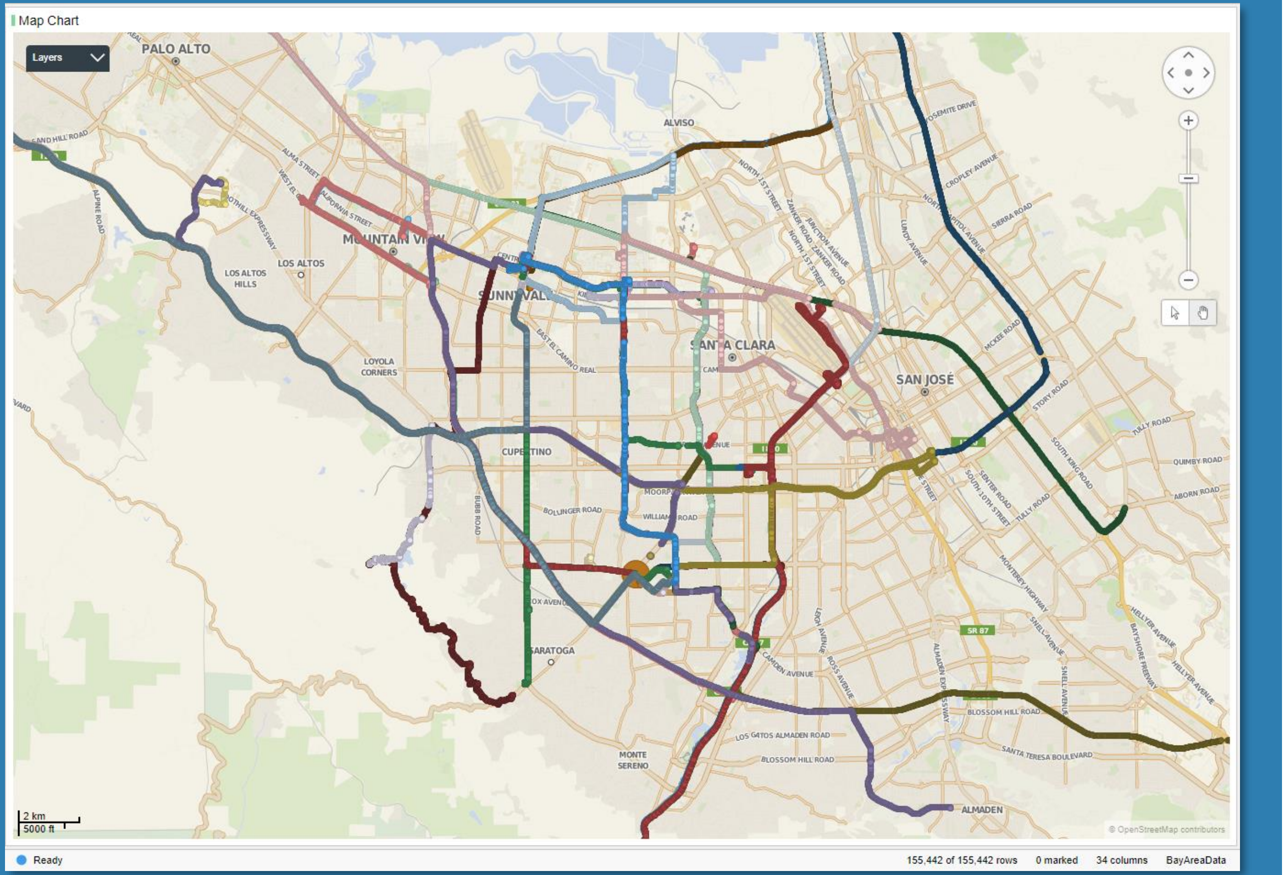
Enabled

© OpenStreetMap contributors | Sudden deceleration events.

Fleet Statistics

Acceleration/Deceleration Events, 2014 - 2017

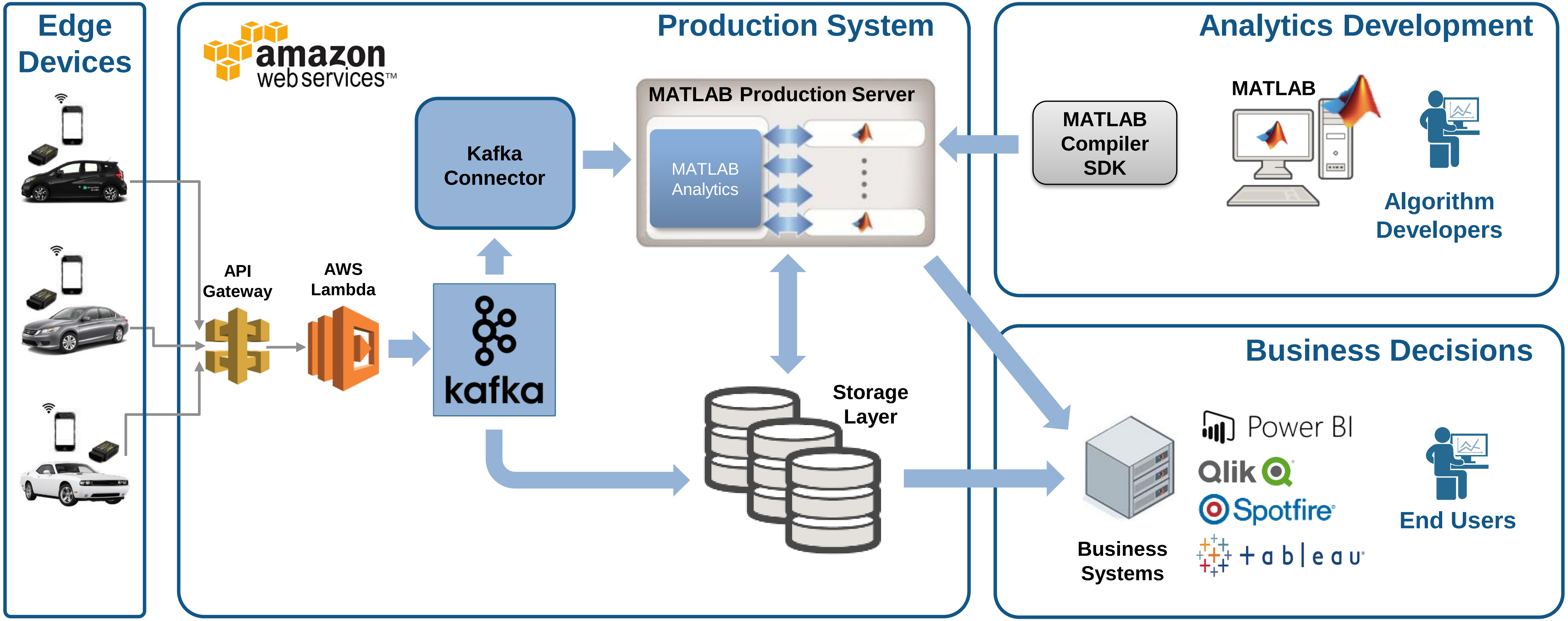
Aggressive deceleration: 11.3%
Safe acceleration: 9.6%
Moderate acceleration: 5.2%
Aggressive acceleration: 3.6%



Map Chart

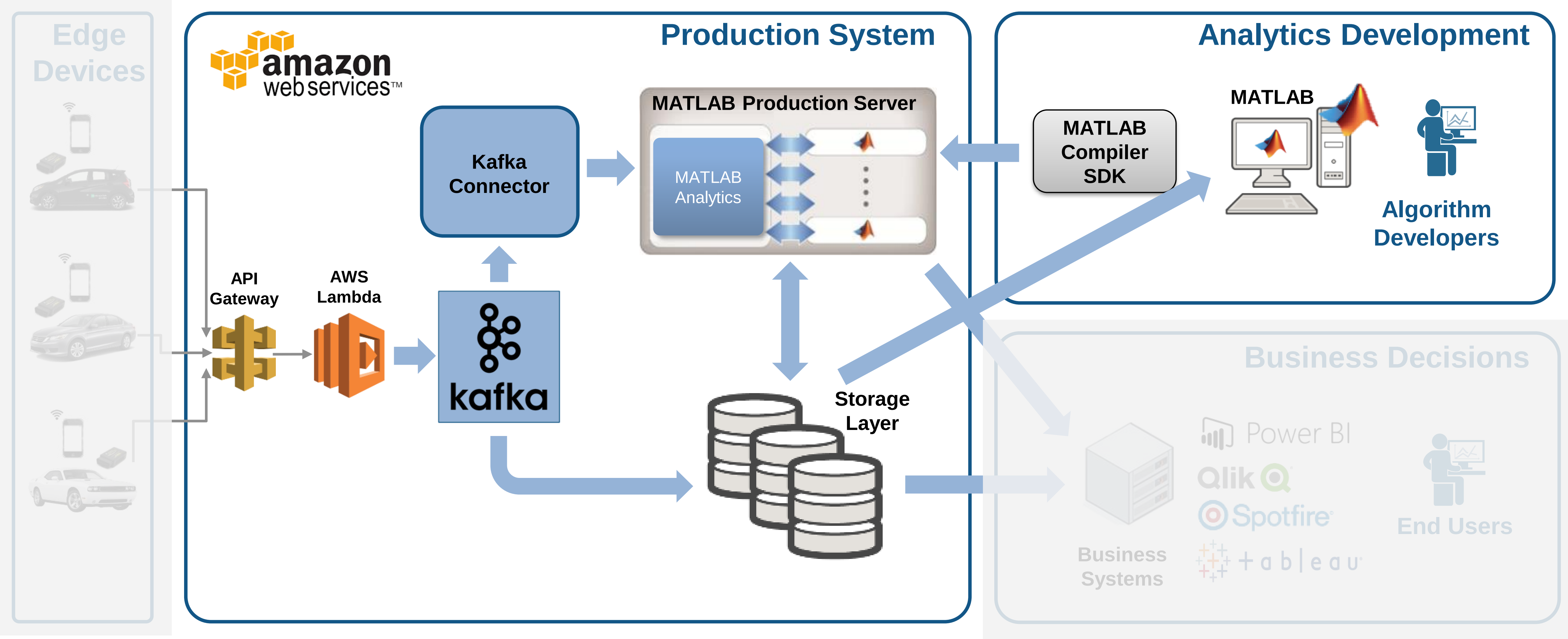
● Ready 155,442 of 155,442 rows 0 marked 34 columns BayAreaData

Fleet Analytics Architecture



1 Access and Explore Data

The first step is to clean up the incoming data



1 Access and Explore Data

The Data: Timestamped messages with JSON encoding

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

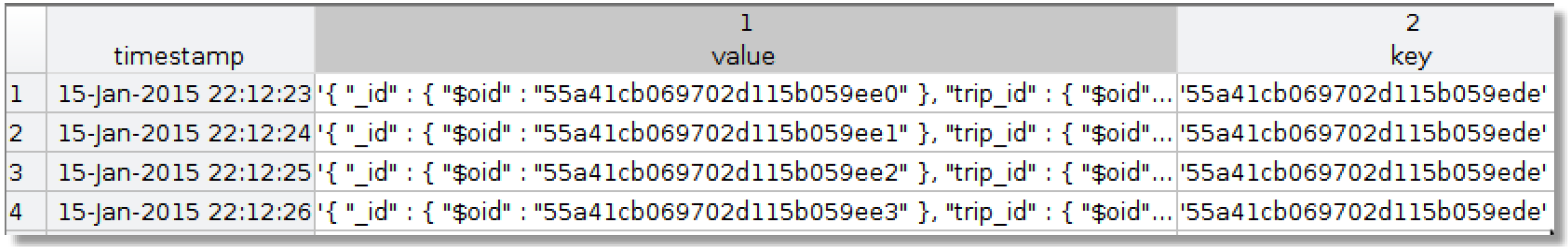
```
{
      "vehicles_id": {"$oid":"55a3fe3569702d5c5c000020"}
      "time":{"$date":"2015-07-13T18:01:53.000Z"},
      "kc” : 2000.0, "kff1225" : 109.65293, "kff125a" : 115.36619,
        …
}
```

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

1 Access and Explore Data

Access a Sample of Data

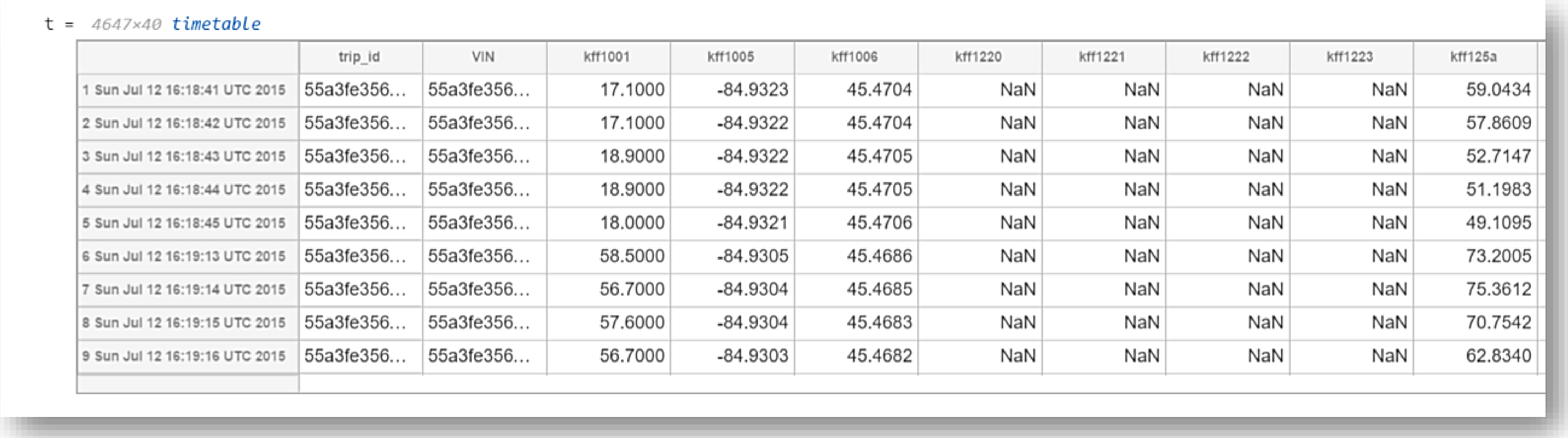
Raw Data



	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



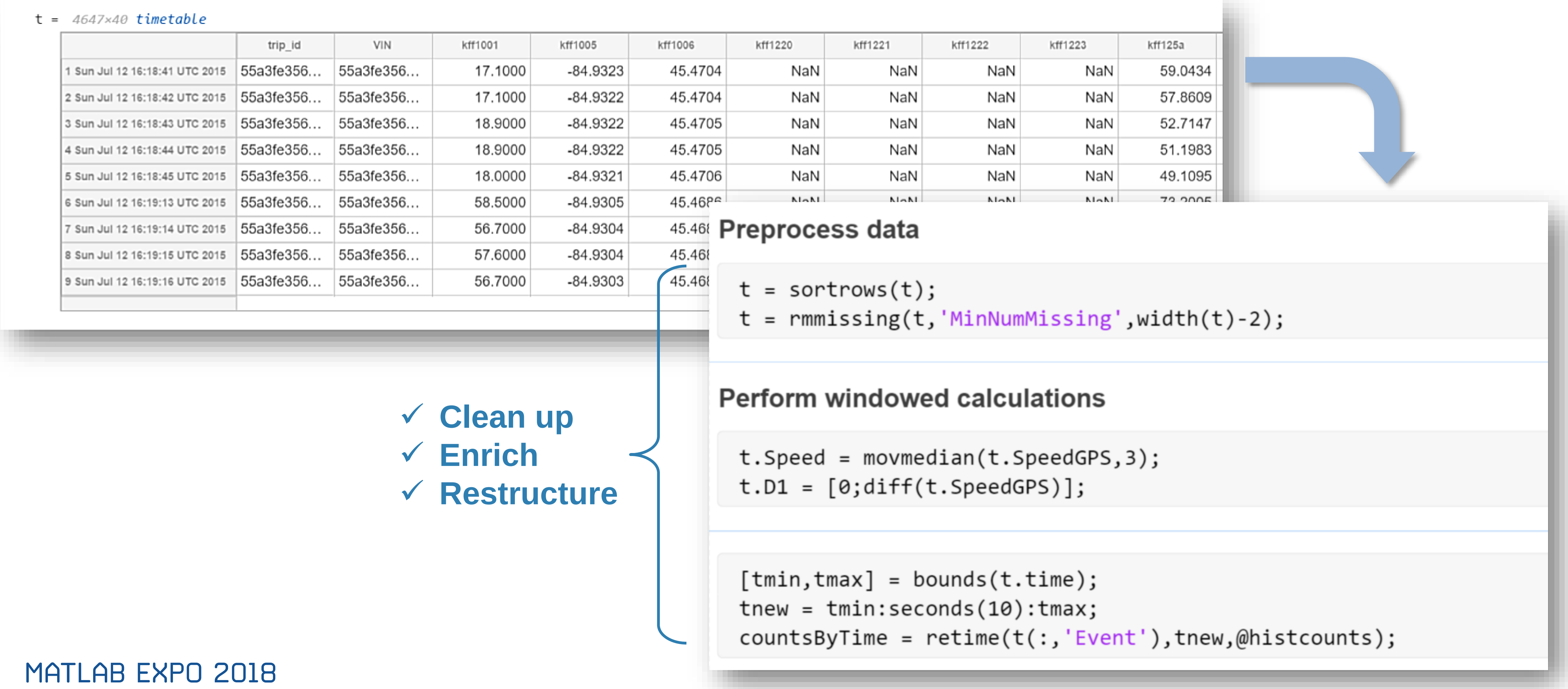
```
t = 4647×40 timetable
```

	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

2 Preprocess Data

Develop a Preprocessing Function

Timetable



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4 Sun Jul 12 16:18:44 UTC 2015	55a3fe356...	55a3fe356...	18.9000	-84.9322	45.4705	NaN	NaN	NaN	NaN	51.1983
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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	45.468					
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					

Preprocess data

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

Perform windowed calculations

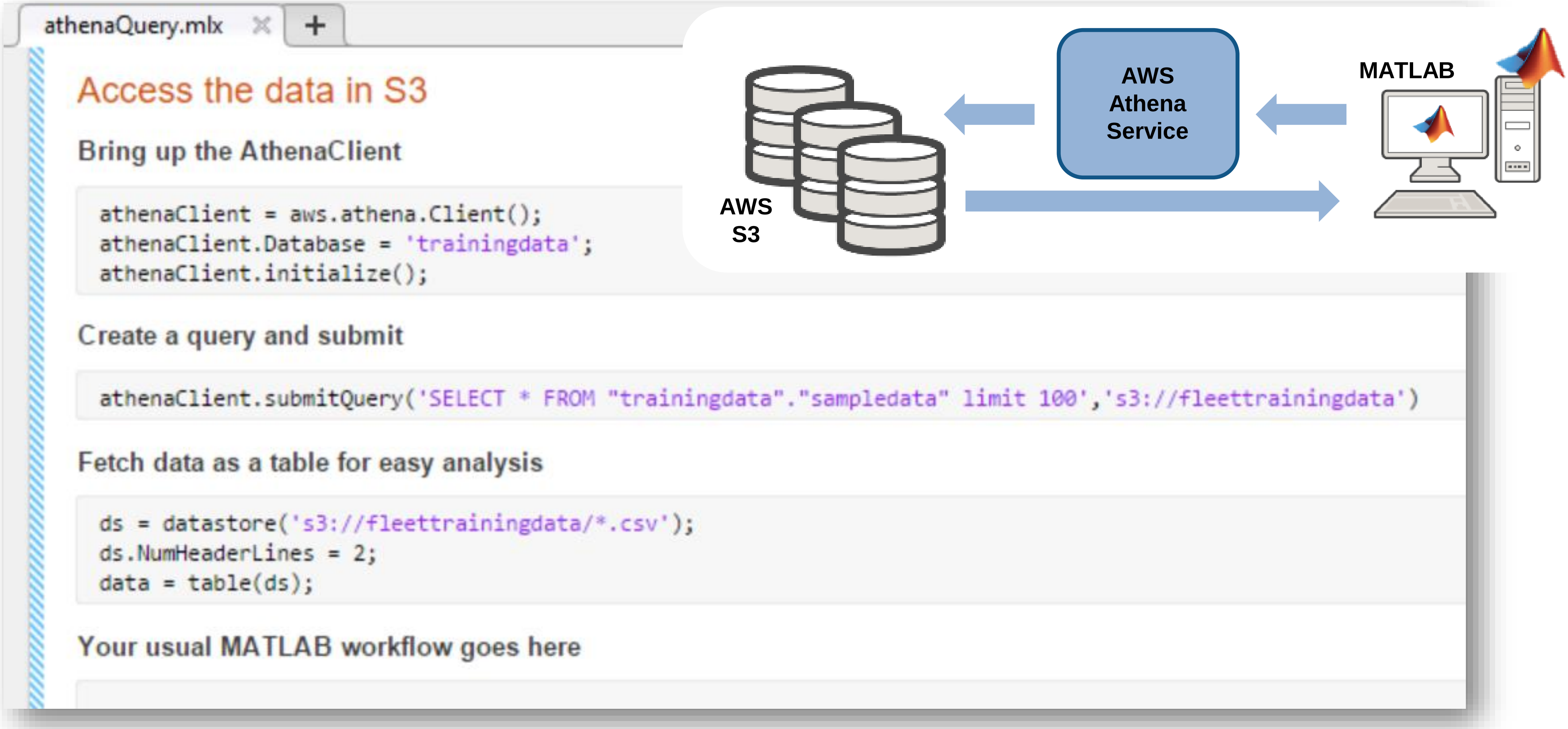
```
t.Speed = movmedian(t.SpeedGPS,3);
t.D1 = [0;diff(t.SpeedGPS)];
```

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

- ✓ Clean up
- ✓ Enrich
- ✓ Restructure

1 Access and Explore Data

Ad Hoc Access to Data from MATLAB



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')
```

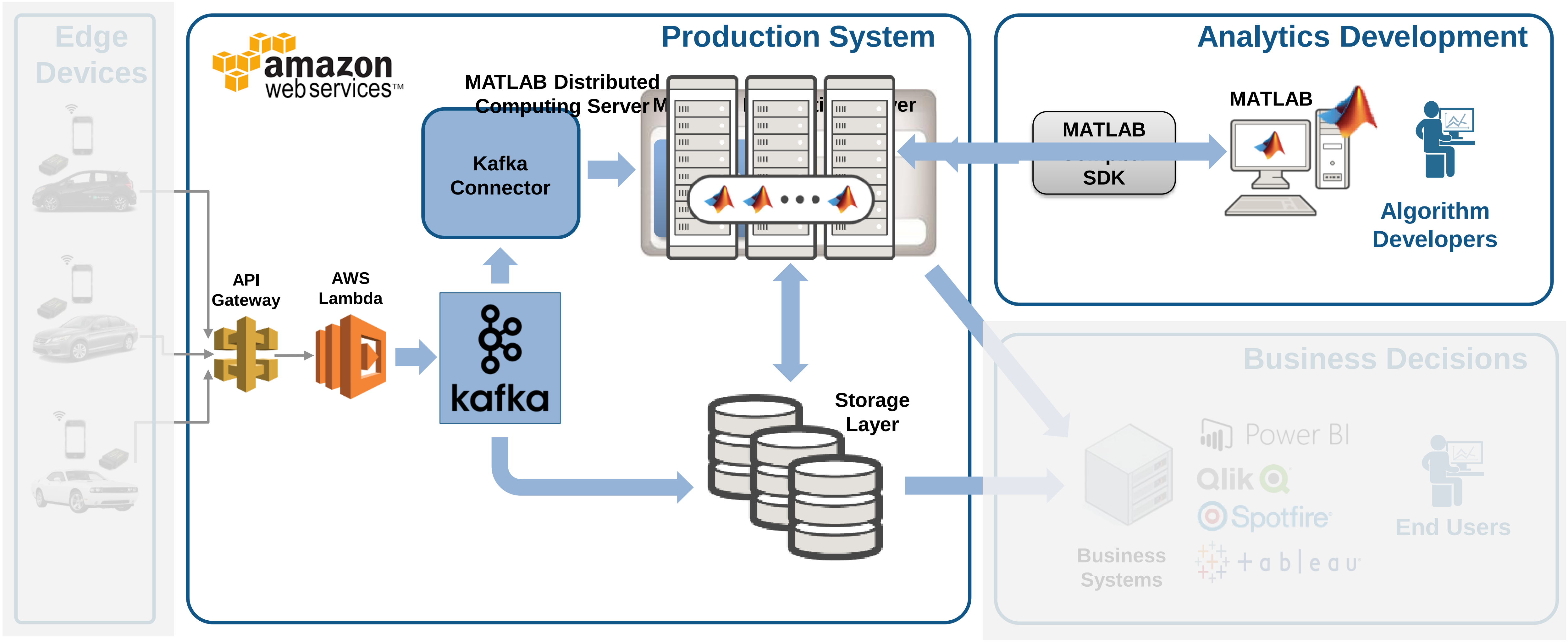
Fetch data as a table for easy analysis

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

Your usual MATLAB workflow goes here

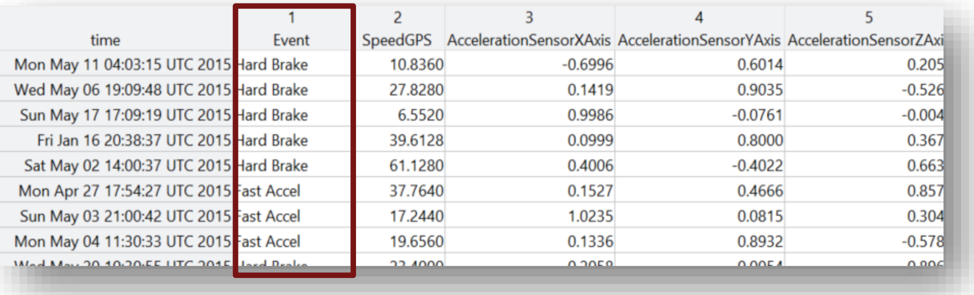
3 Develop Predictive Models

Develop a Predictive Model



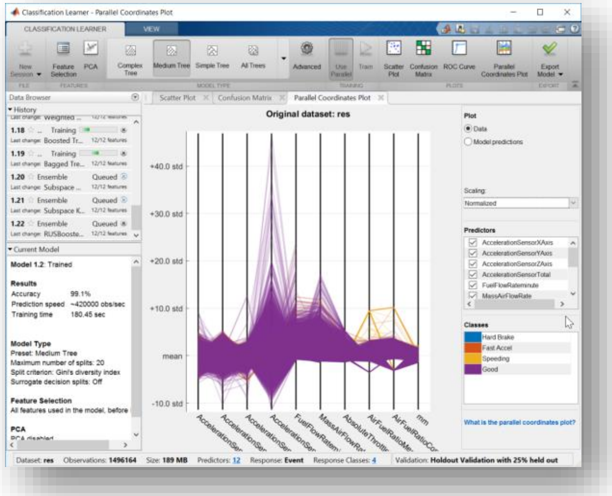
3 Develop Predictive Models

Everything you need to develop a predictive model is found in MATLAB



	1	2	3	4	5
time	Event	SpeedGPS	AccelerationSensorXAxis	AccelerationSensorYAxis	AccelerationSensorZAxi
Mon May 11 04:03:15 UTC 2015	Hard Brake	10.8360	-0.6996	0.6014	0.205
Wed May 06 19:09:48 UTC 2015	Hard Brake	27.8280	0.1419	0.9035	-0.526
Sun May 17 17:09:19 UTC 2015	Hard Brake	6.5520	0.9986	-0.0761	-0.004
Fri Jan 16 20:38:37 UTC 2015	Hard Brake	39.6128	0.0999	0.8000	0.367
Sat May 02 14:00:37 UTC 2015	Hard Brake	61.1280	0.4006	-0.4022	0.663
Mon Apr 27 17:54:27 UTC 2015	Fast Accel	37.7640	0.1527	0.4666	0.857
Sun May 03 21:00:42 UTC 2015	Fast Accel	17.2440	1.0235	0.0815	0.304
Mon May 04 11:30:33 UTC 2015	Fast Accel	19.6560	0.1336	0.8932	-0.578
Wed May 20 10:20:55 UTC 2015	Hard Brake	22.4000	0.2058	0.0054	0.806

Label Events



Classification Learner - Parallel Coordinates Plot

Model 1.2: Trained

Results
Accuracy 99.1%
Prediction speed ~420000 obs/sec
Training time 180.45 sec

Model Type
Preset: Medium Tree
Maximum number of splits: 20
Split criterion: Gini's diversity index
Surrogate decision splits: Off

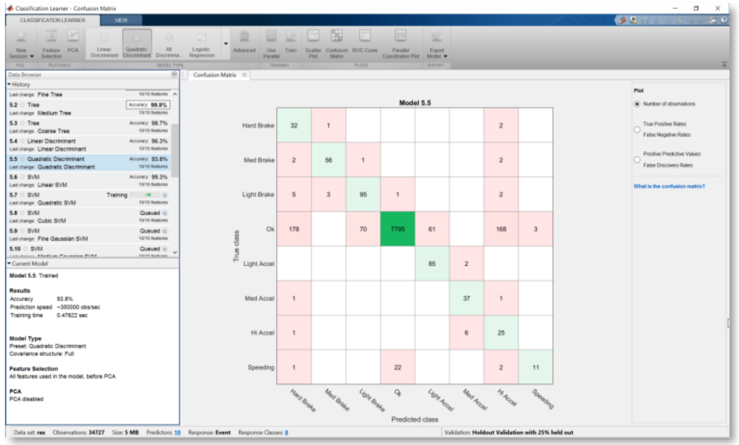
Feature Selection
All features used in the model, before

PCA
PCA disabled

Dataset: res Observations: 1496164 Size: 189 MB Predictors: 12 Response: Event Response Classes: 4 Validation: Holdout Validation with 25% held out

Represent Signals

Train Model



Classification Learner - Confusion Matrix

Model 5.5	Hard Brake	Med Brake	Light Brake	Ok	Light Accel	Med Accel	Hi Accel	Speeding
Hard Brake	32	1					2	
Med Brake	2	56	1				2	
Light Brake	5	3	95	1			2	
Ok	178		70	7796	61		168	3
Light Accel					85	2		
Med Accel	1					37	1	
Hi Accel	1					6	25	
Speeding	1			22			2	11

Model 5.5: Trained

Results
Accuracy 93.8%
Prediction speed ~360000 obs/sec
Training time 0.47822 sec

Model Type
Preset: Quadratic Discriminant
Covariance structure: Full

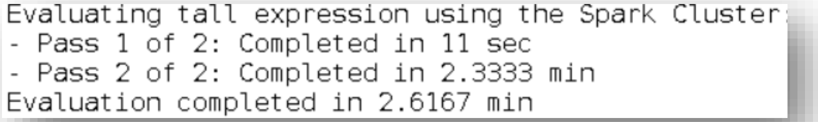
Feature Selection
All features used in the model, before PCA

PCA
PCA disabled

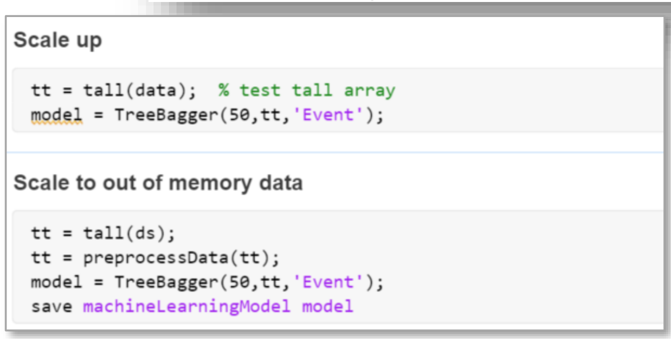
Data set: res Observations: 34727 Size: 5 MB Predictors: 10 Response: Event Response Classes: 8 Validation: Holdout Validation with 25% held out

CLASSIFICATION LEARNER
VIEW
New Session
Feature Selection
PCA
Linear Discriminant
Quadratic Discriminant
All Discrimina...
Logistic Regression
Advanced
Use Parallel
Train
Scatter Plot
Confusion Matrix
ROC Curve
Parallel Coordinates Plot
Export Model
Data Browser
History
Last change: Fine Tree 10/10 features
5.2 Tree Accuracy: 99.9% Last change: Medium Tree 10/10 features
5.3 Tree Accuracy: 98.7% Last change: Coarse Tree 10/10 features
5.4 Linear Discriminant Accuracy: 96.3% Last change: Linear Discriminant 10/10 features
5.5 Quadratic Discriminant Accuracy: 93.8% Last change: Quadratic Discriminant 10/10 features
5.6 SVM Accuracy: 99.3% Last change: Linear SVM 10/10 features
5.7 SVM Training Last change: Quadratic SVM 10/10 features
5.8 SVM Queued Last change: Cubic SVM 10/10 features
5.9 SVM Queued Last change: Fine Gaussian SVM 10/10 features
5.10 SVM Queued
Current Model
True class
Predicted class
Plot
Number of observations
True Positive Rates
False Negative Rates
Positive Predictive Values
False Discovery Rates
What is the confusion matrix?

Validate Model



```
Evaluating tall expression using the Spark Cluster:
- Pass 1 of 2: Completed in 11 sec
- Pass 2 of 2: Completed in 2.3333 min
Evaluation completed in 2.6167 min
```



Scale up

```
tt = tall(data);  % test tall array
model = TreeBagger(50,tt,'Event');
```

Scale to out of memory data

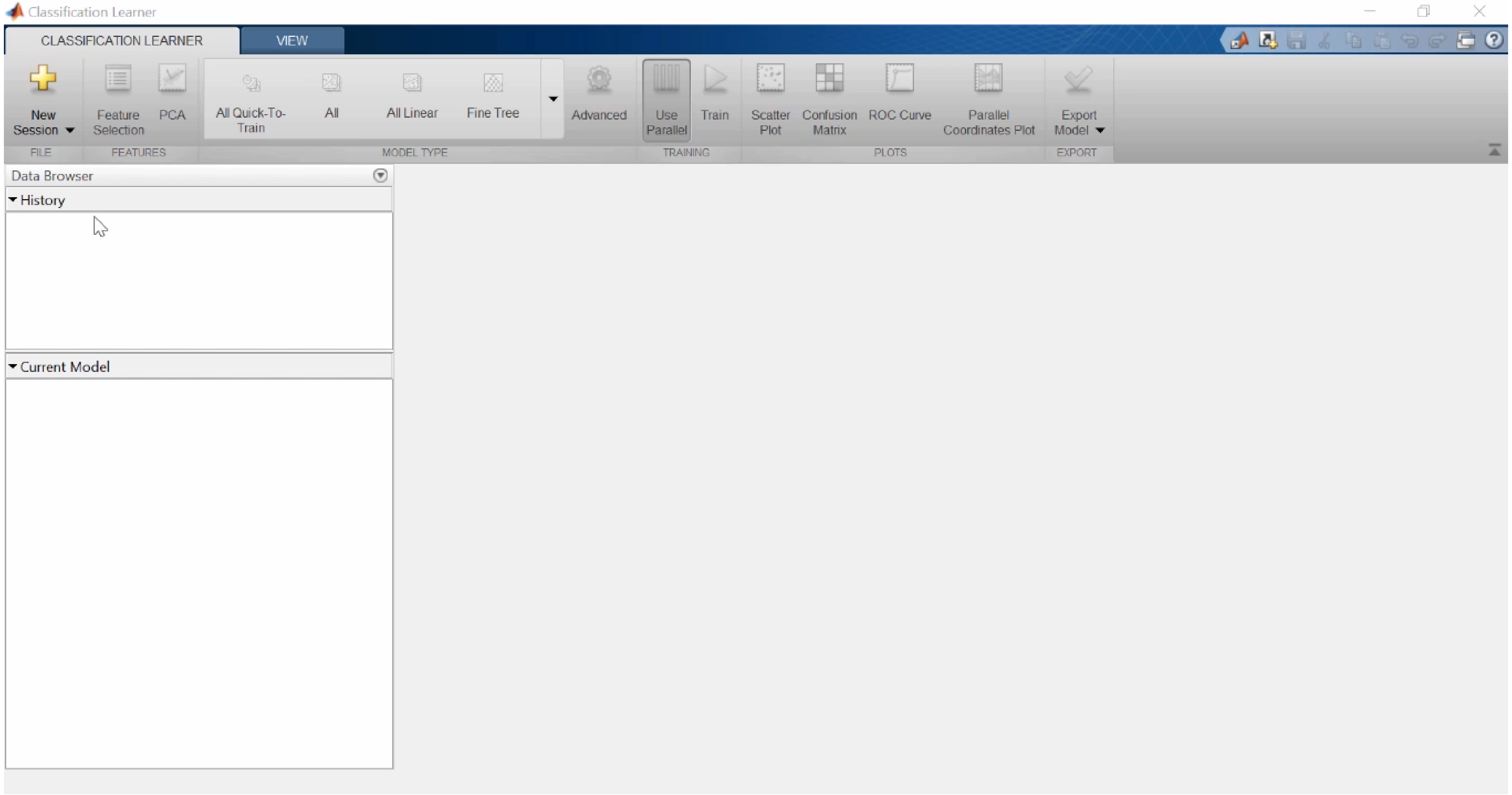
```
tt = tall(ds);
tt = preprocessData(tt);
model = TreeBagger(50,tt,'Event');
save machineLearningModel model
```

Scale Up

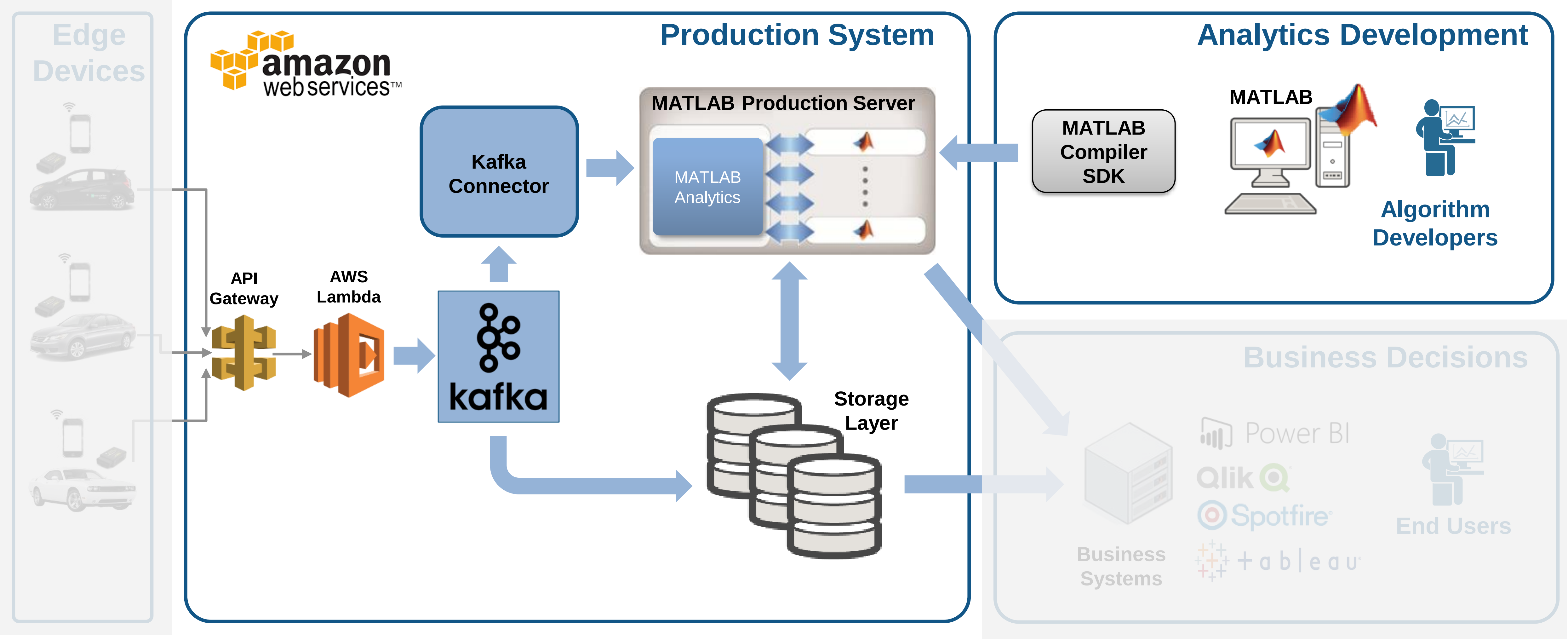
3

Develop Predictive Models

Develop a Predictive Model in MATLAB

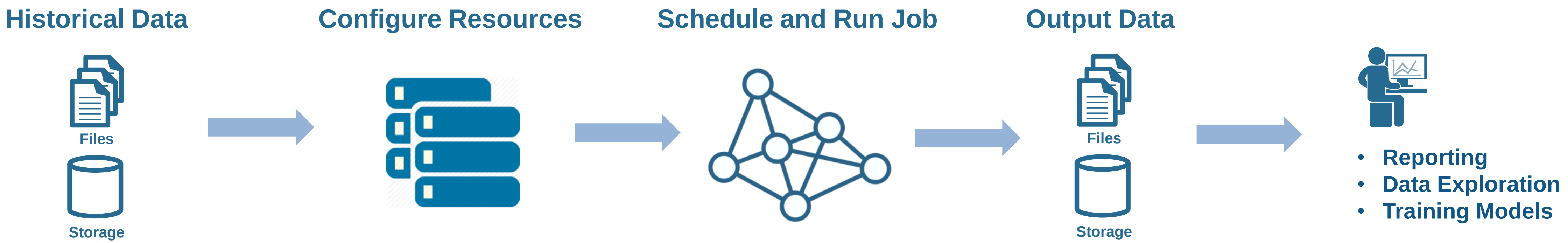


Integrate Analytics with Production Systems

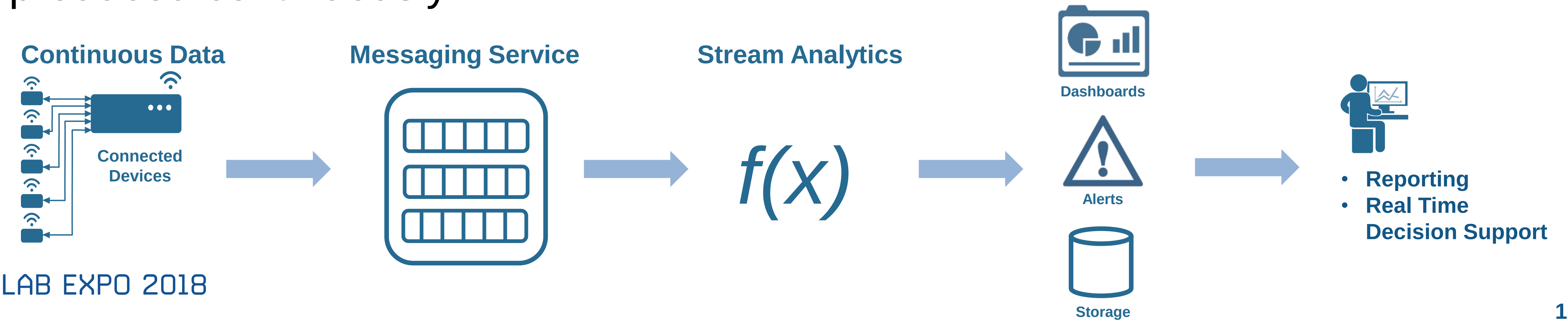


A quick Intro to Stream Processing

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

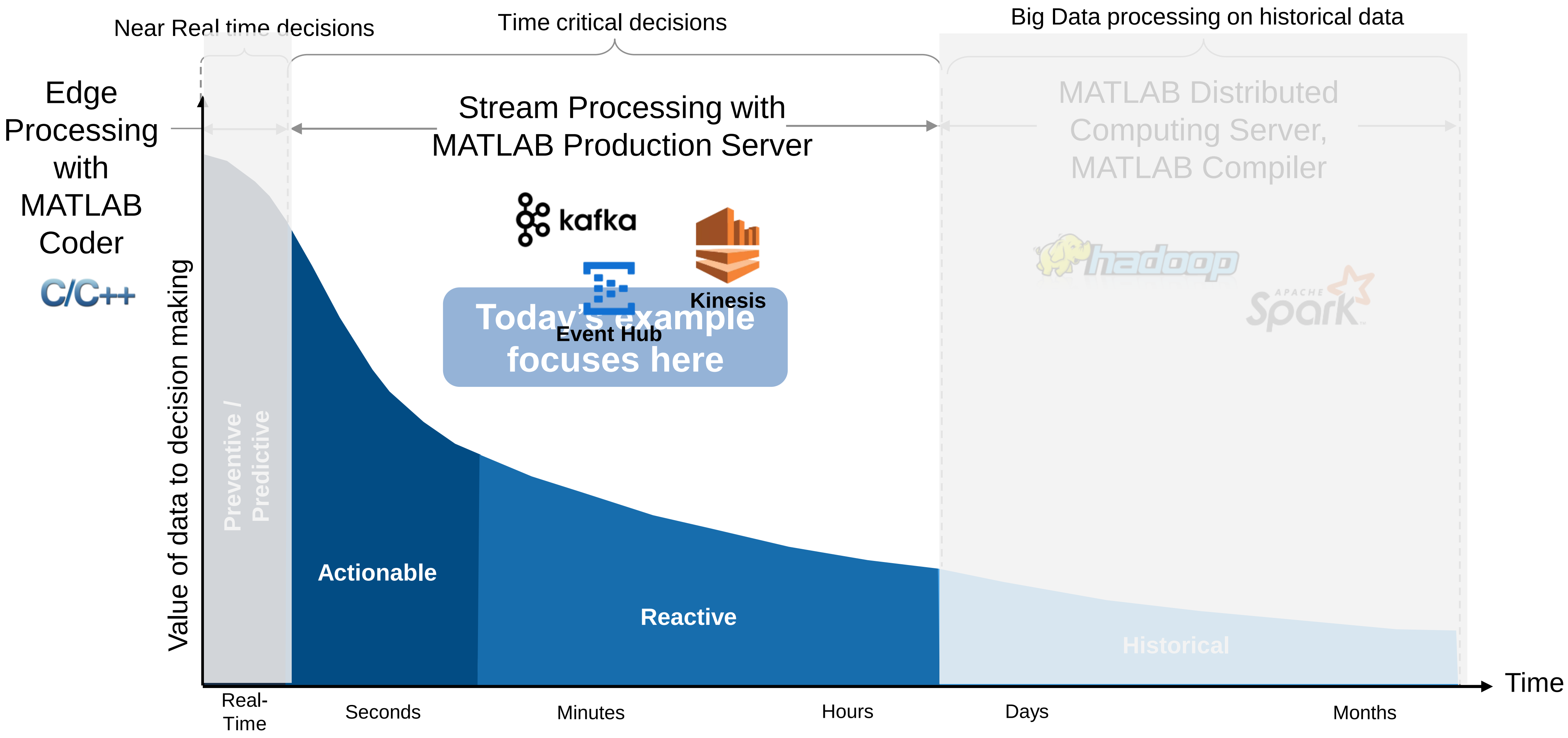


- ***Stream Processing*** applies computation to an unbounded data set that is produced continuously



4 Integrate with Production Systems

Why stream processing?



Near Real time decisions

Time critical decisions

Big Data processing on historical data

Edge Processing with MATLAB Coder

C/C++

Stream Processing with MATLAB Production Server

kafka

Kinesis

Event Hub

Today's example focuses here

MATLAB Distributed Computing Server, MATLAB Compiler

hadoop

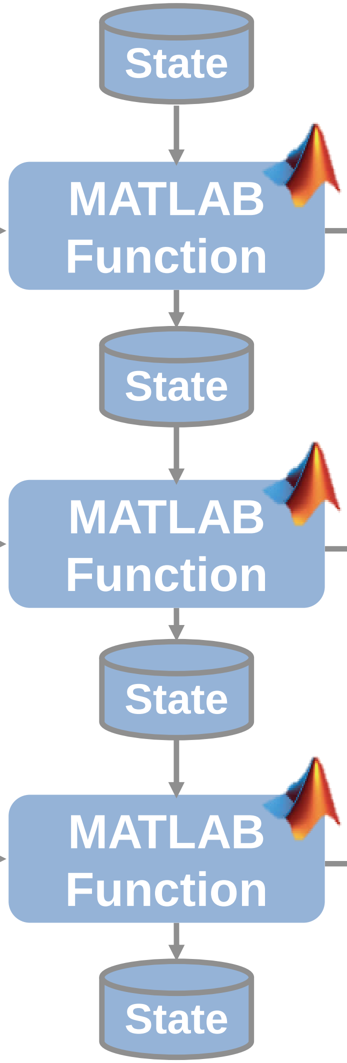
APACHE Spark

4 Integrate 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

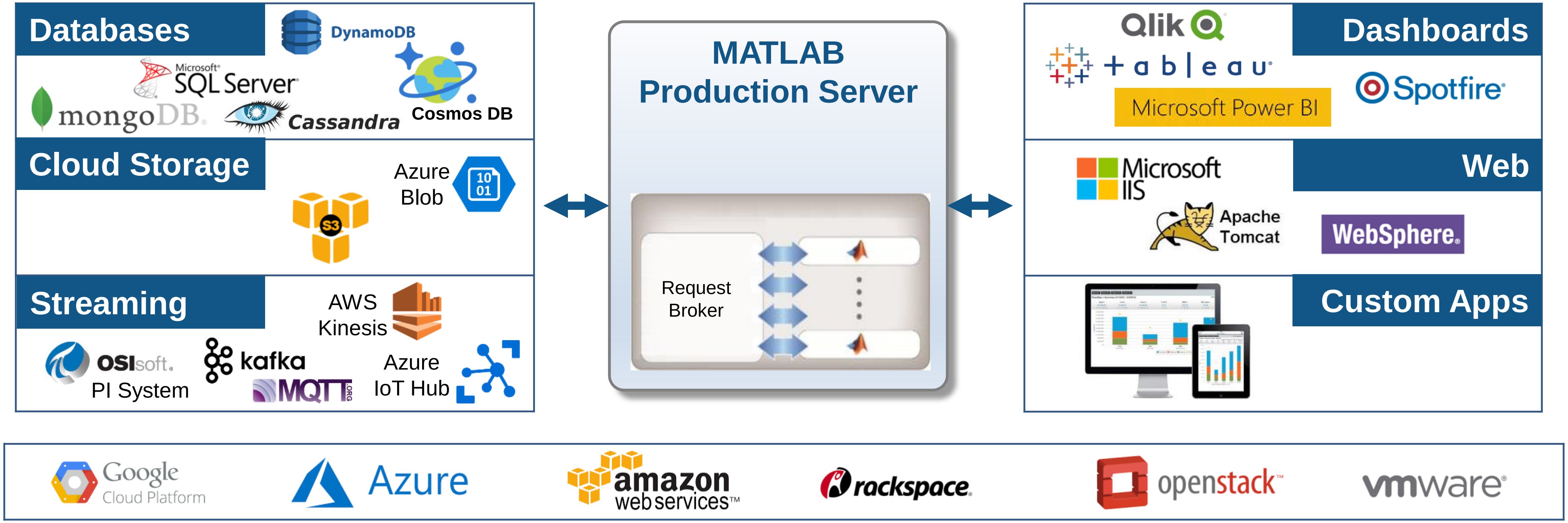
Time window		Vehicle	Score
…		…	…
18:00:00	18:10:00	55a3fd	5
		55a3fe	…
		55a419	…
18:10:00	18:20:00	55a3fd	7
		55a3fe	3
		55a419	…
18:20:00	18:30:00	55a3fd	…
		55a3fe	4
		55a419	…
18:30:00	18:40:00	55a3fd	…
		55a3fe	5
		55a419	8

Introducing MATLAB Production Server

Data

Analytics

Business System



Databases

DynamoDB

Microsoft SQL Server

mongoDB

Cassandra

Cosmos DB

Cloud Storage

Azure Blob

S3

Streaming

AWS Kinesis

OSIsoft PI System

kafka

MQTT

Azure IoT Hub

MATLAB Production Server

Request Broker

Dashboards

Qlik

tableau

Microsoft Power BI

Spotfire

Web

Microsoft IIS

Apache Tomcat

WebSphere

Custom Apps

Google Cloud Platform

Azure

amazon web services

rackspace

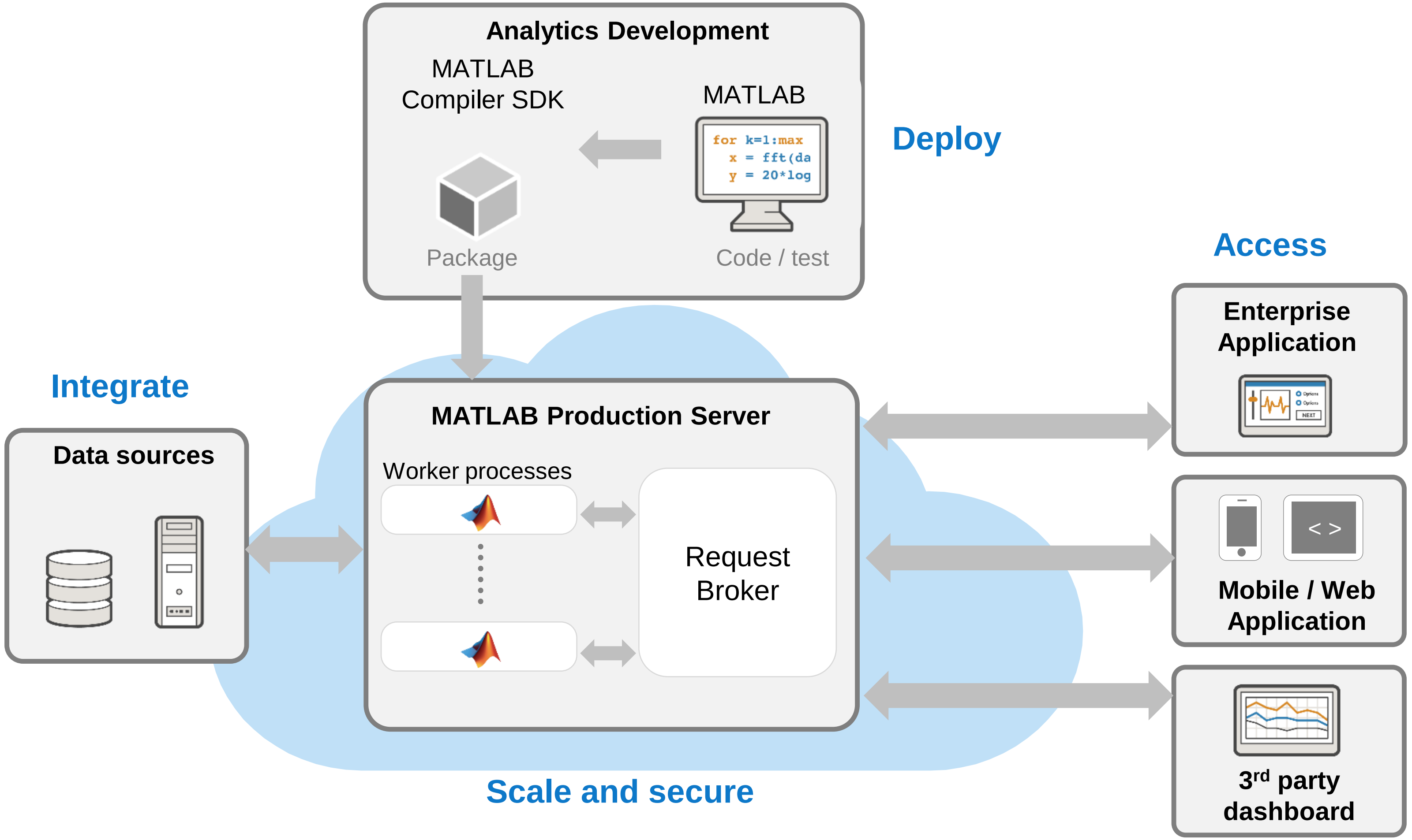
openstack

vmware

Platform

4 Integrate with Production Systems

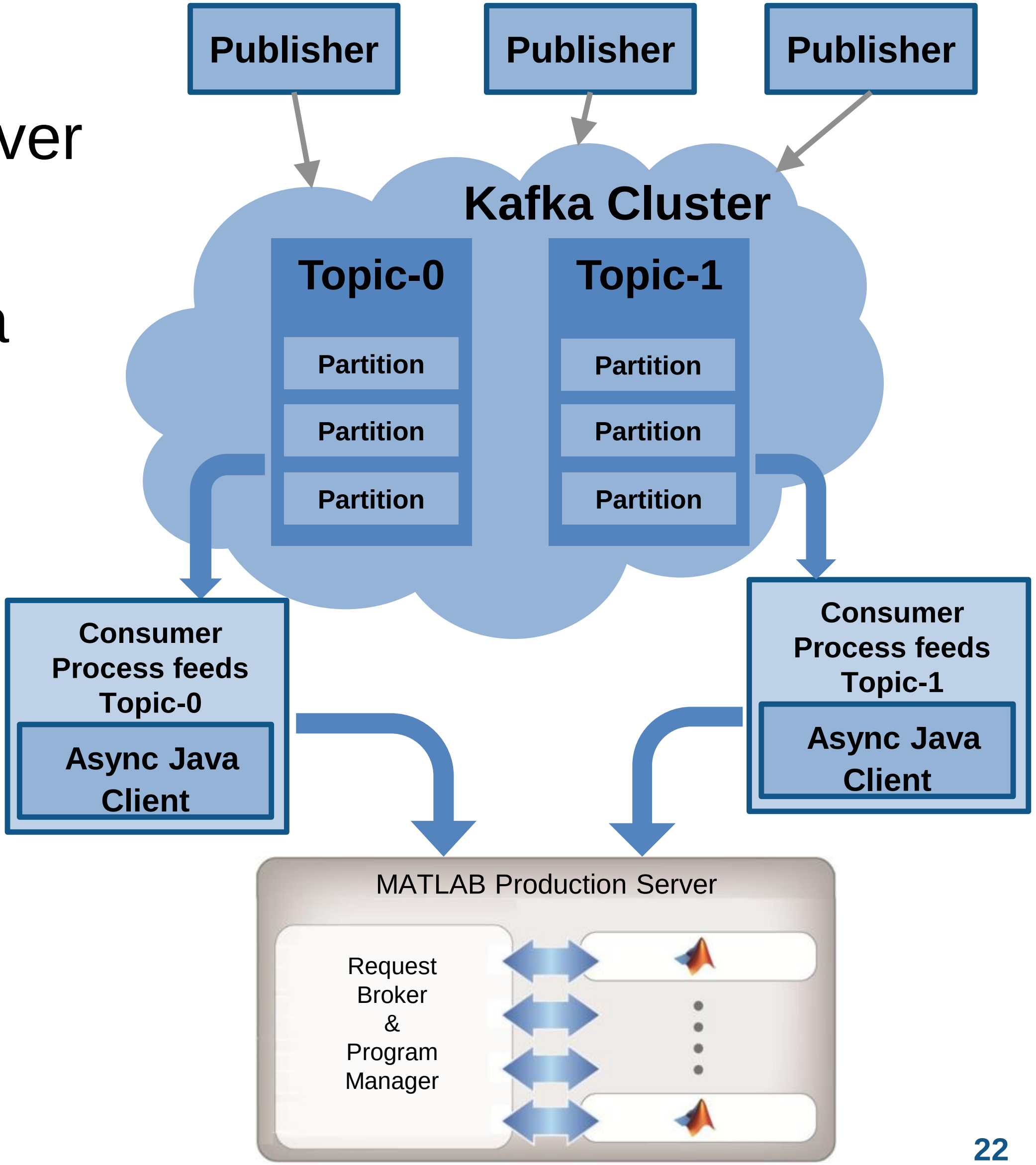
MATLAB Production Server is an application server that publishes MATLAB code as APIs



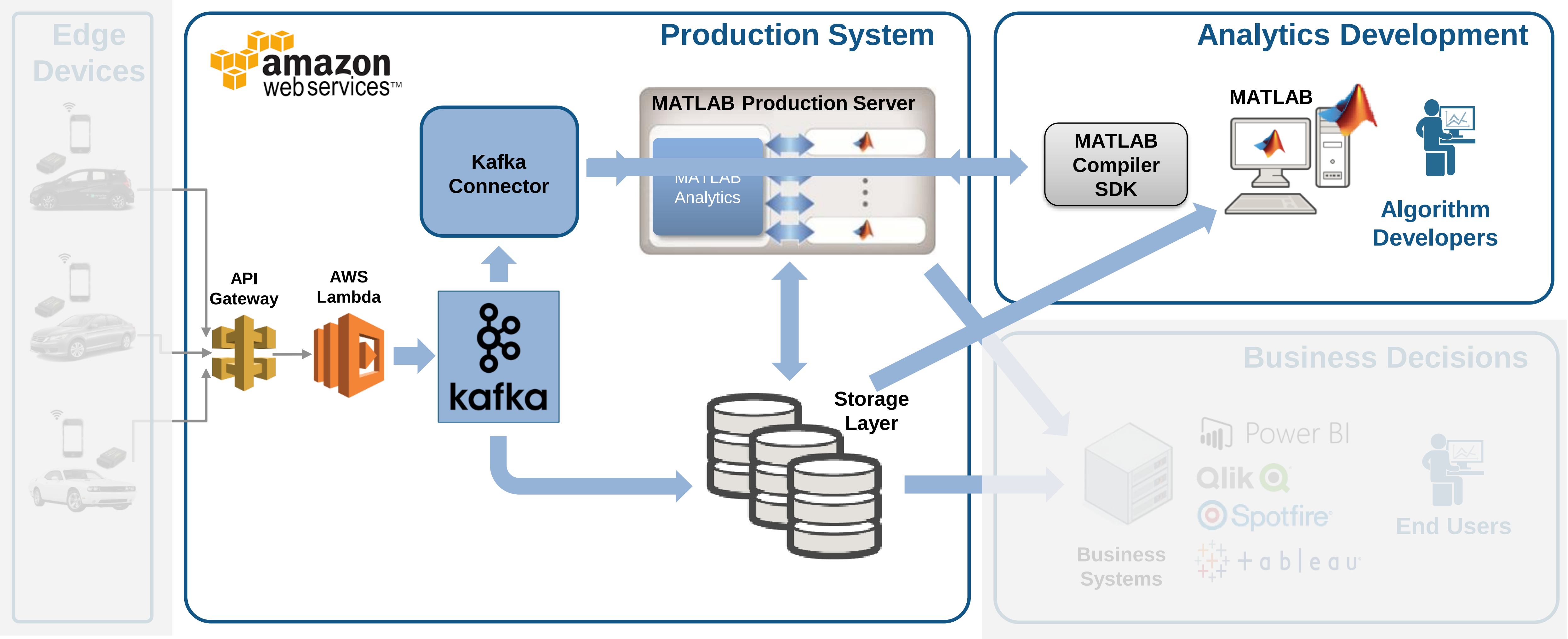
4 Integrate with Production Systems

Connecting MATLAB Production Server to Kafka

- Kafka client for MATLAB Production Server feeds topics to functions deployed on the server
- Configurable batch of messages passed as a MATLAB Timetable
- Each consumer process feeds one topic to a specified function
- Drive everything from a simple config file
  - No programming outside of MATLAB!

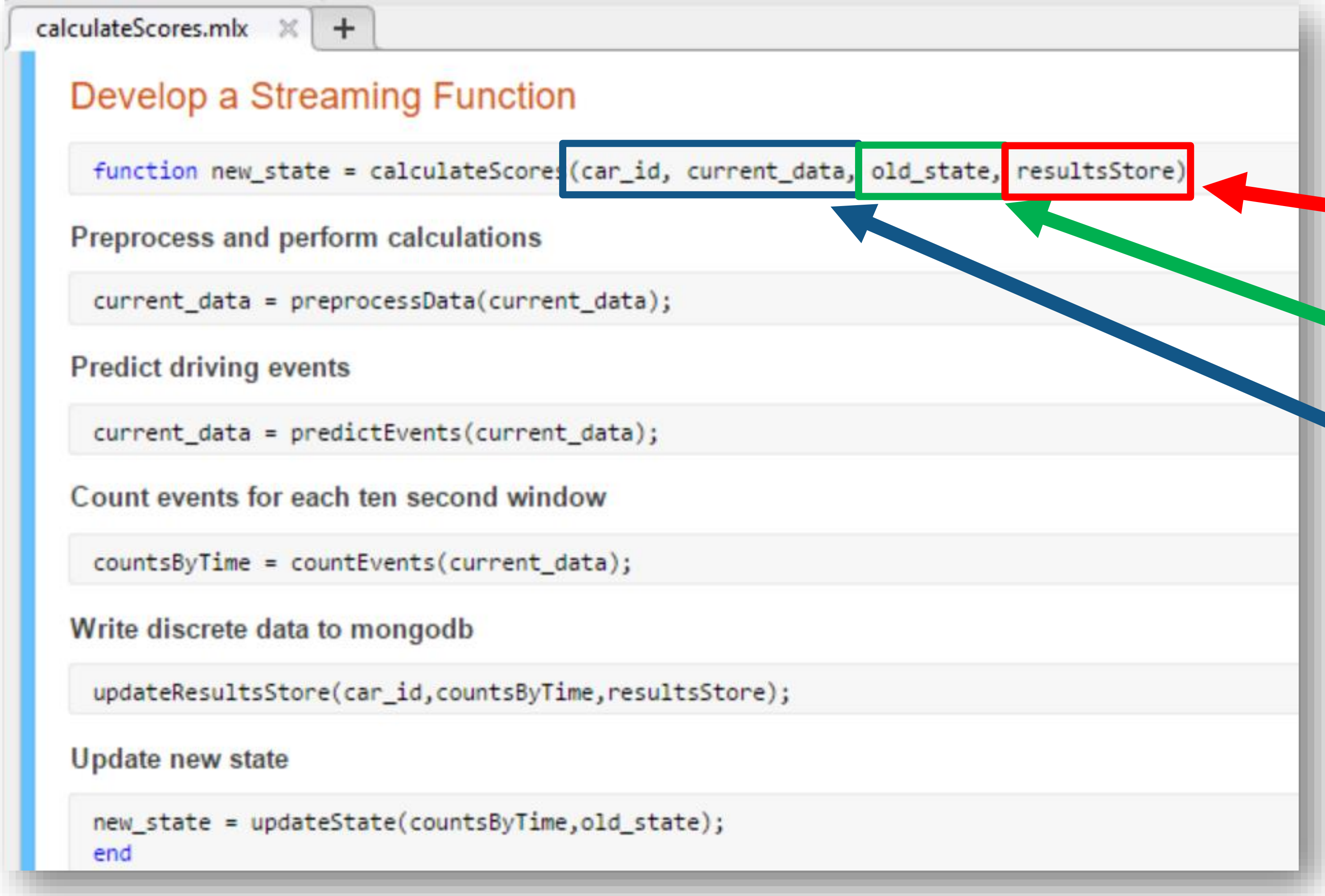


Develop and Deploy a Stream Processing Function



4 Integrate with Production Systems

Develop a Stream Processing Function in MATLAB



Develop a Streaming Function

```
function new_state = calculateScores(car_id, current_data, old_state, resultsStore)
```

Preprocess and perform calculations

```
current_data = preprocessData(current_data);
```

Predict driving events

```
current_data = predictEvents(current_data);
```

Count events for each ten second window

```
countsByTime = countEvents(current_data);
```

Write discrete data to mongodb

```
updateResultsStore(car_id,countsByTime,resultsStore);
```

Update new state

```
new_state = updateState(countsByTime,old_state);
end
```

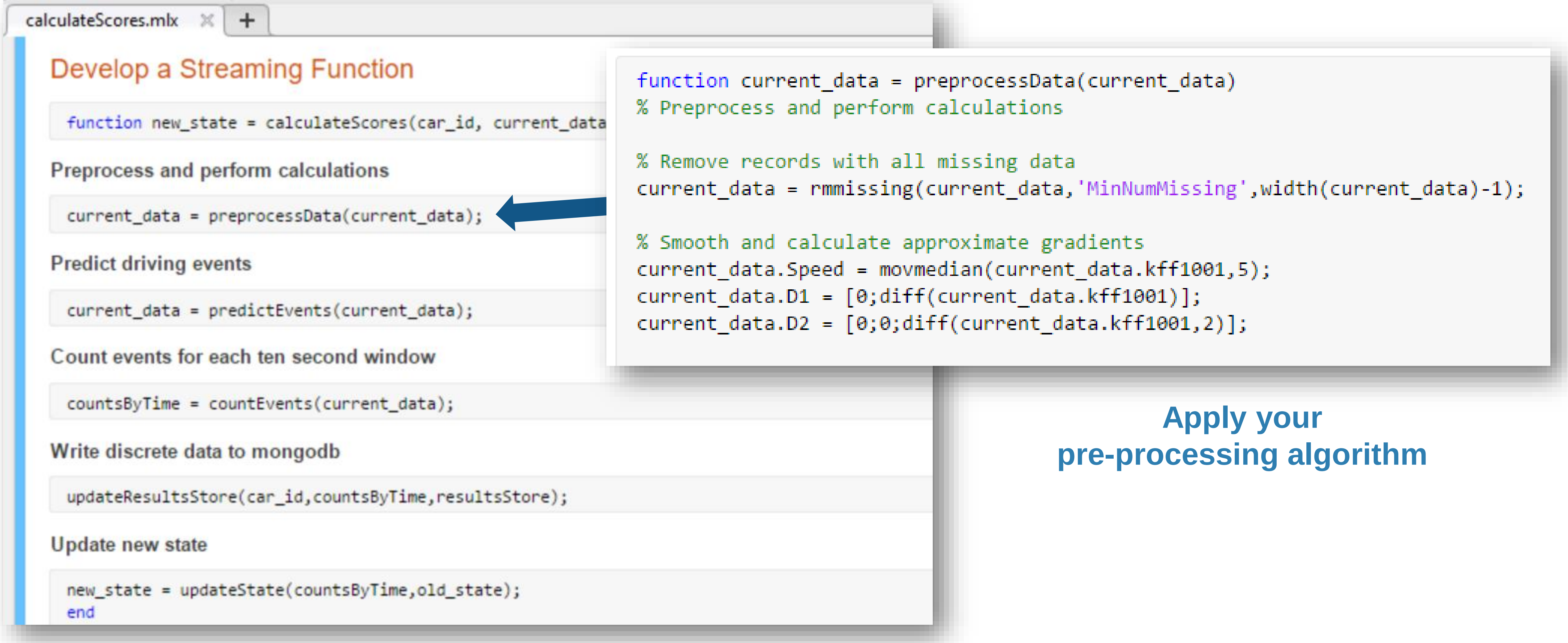
Process each window of data as it arrives

Current score

Previous state

Current window of data to be processed

Develop a Stream Processing Function in MATLAB



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```

Update new state

```
new_state = updateState(countsByTime,old_state);
end
```

```
function current_data = preprocessData(current_data)
% Preprocess and perform calculations

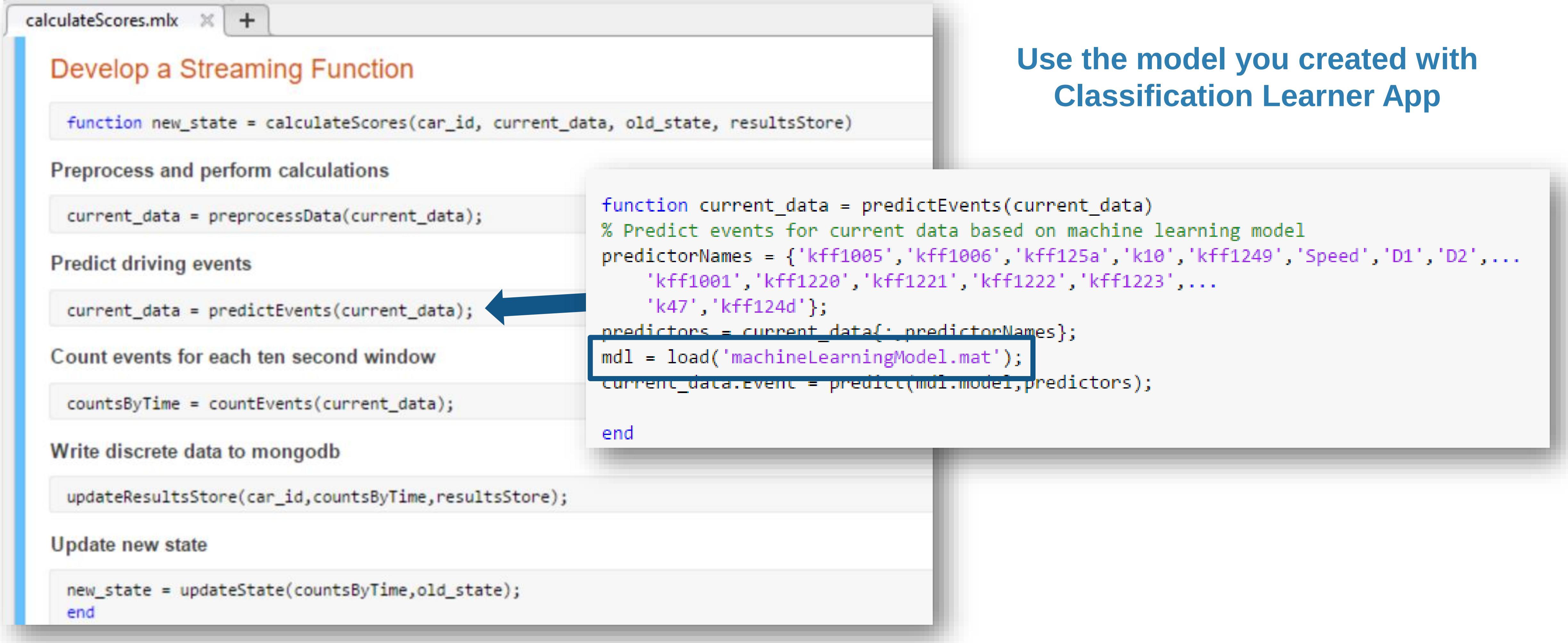
% Remove records with all missing data
current_data = rmmissing(current_data,'MinNumMissing',width(current_data)-1);

% Smooth and calculate approximate gradients
current_data.Speed = movmedian(current_data.kff1001,5);
current_data.D1 = [0;diff(current_data.kff1001)];
current_data.D2 = [0;0;diff(current_data.kff1001,2)];
```

Apply your pre-processing algorithm

4 Integrate with Production Systems

Develop a Stream Processing Function in MATLAB



calculateScores.mlx

Develop a Streaming Function

```
function new_state = calculateScores(car_id, current_data, old_state, resultsStore)
```

Preprocess and perform calculations

```
current_data = preprocessData(current_data);
```

Predict driving events

```
current_data = predictEvents(current_data);
```

Count events for each ten second window

```
countsByTime = countEvents(current_data);
```

Write discrete data to mongodb

```
updateResultsStore(car_id,countsByTime,resultsStore);
```

Update new state

```
new_state = updateState(countsByTime,old_state);
end
```

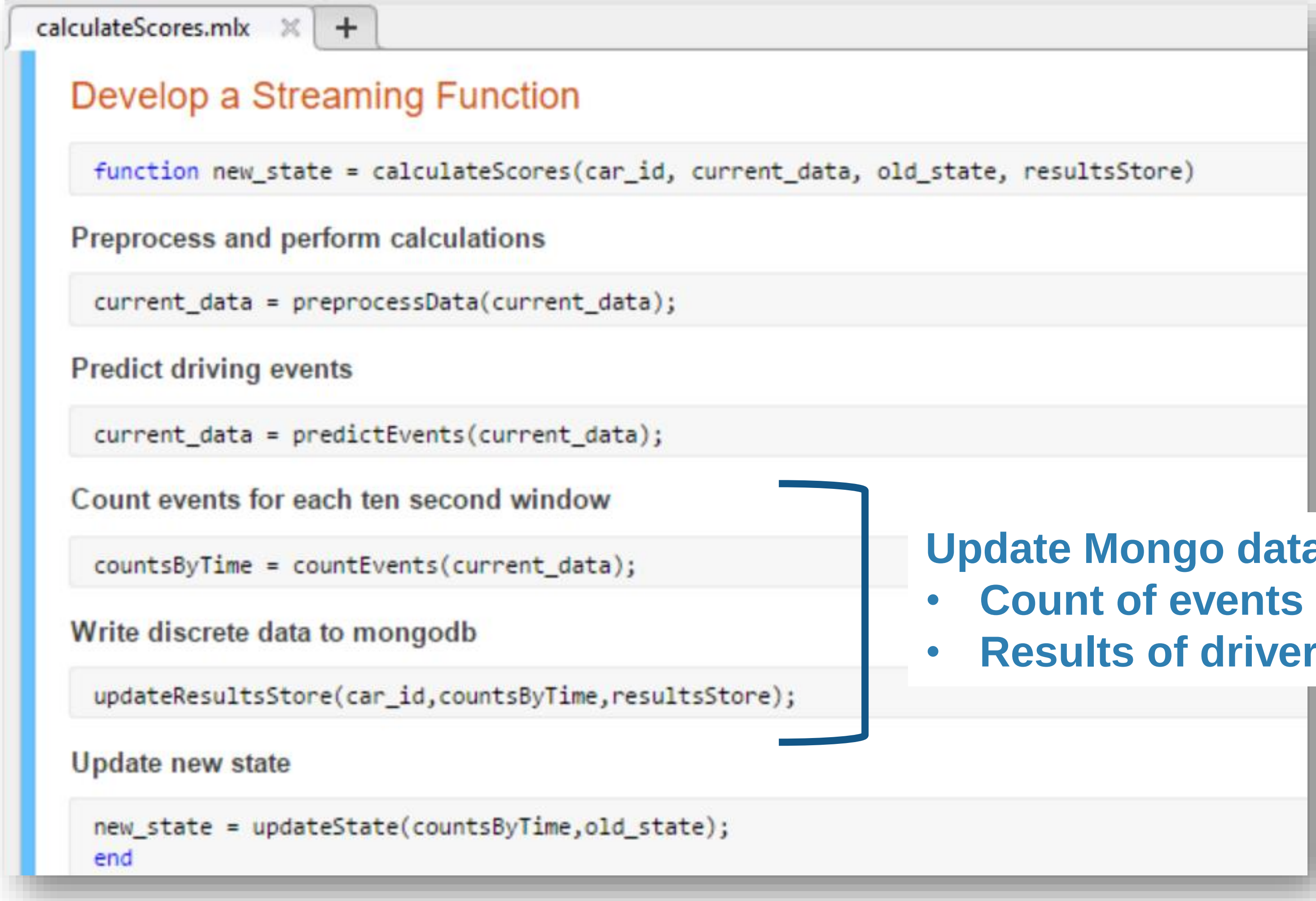
```
function current_data = predictEvents(current_data)
% Predict events for current data based on machine learning model
predictorNames = {'kff1005','kff1006','kff125a','k10','kff1249','Speed','D1','D2',...
    'kff1001','kff1220','kff1221','kff1222','kff1223',...
    'k47','kff124d'};
predictors = current_data{:,predictorNames};
mdl = load('machineLearningModel.mat');
current_data.Event = predict(mdl.model,predictors);

end
```

Use the model you created with Classification Learner App

4 Integrate with Production Systems

Develop a Stream Processing Function in MATLAB



Develop a Streaming Function

```
function new_state = calculateScores(car_id, current_data, old_state, resultsStore)
```

Preprocess and perform calculations

```
current_data = preprocessData(current_data);
```

Predict driving events

```
current_data = predictEvents(current_data);
```

Count events for each ten second window

```
countsByTime = countEvents(current_data);
```

Write discrete data to mongodb

```
updateResultsStore(car_id,countsByTime,resultsStore);
```

Update new state

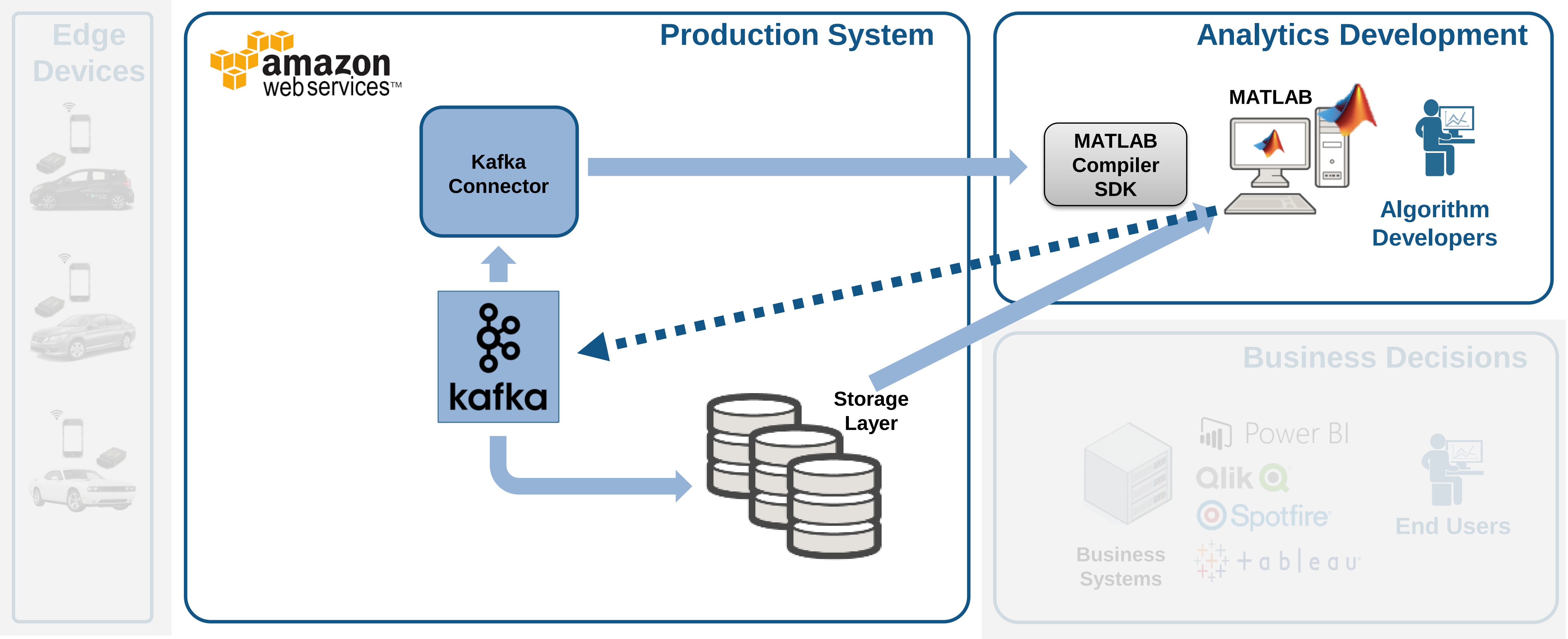
```
new_state = updateState(countsByTime,old_state);
end
```

Update Mongo database

- Count of events by type and location
- Results of driver scoring

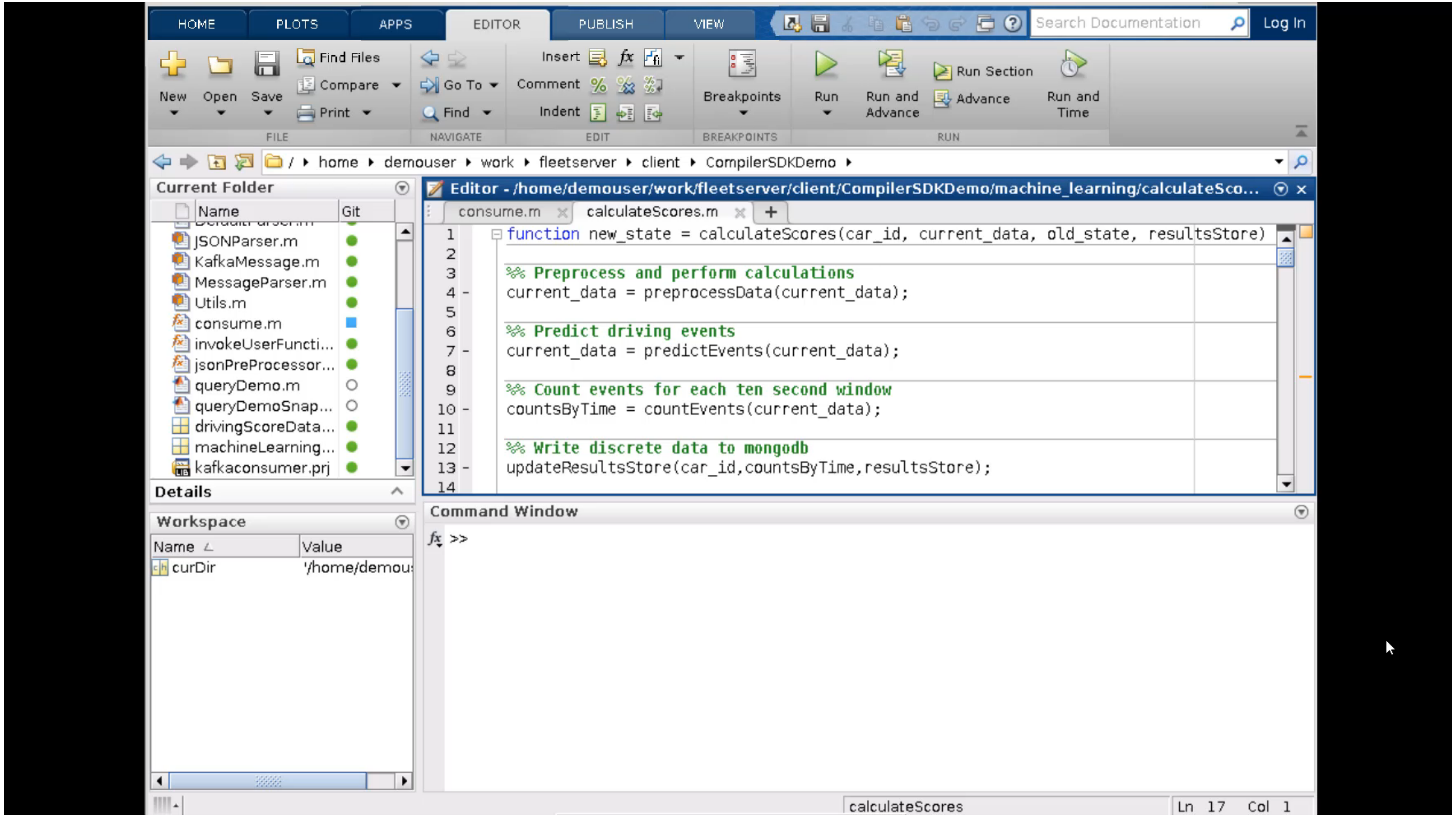
4 Integrate with Production Systems

Debug a Stream Processing Function in MATLAB



4 Integrate with Production Systems

Debug a Stream Processing Function in MATLAB



Editor - /home/demouser/work/fleetserver/client/CompilerSDKDemo/machine_learning/calculateSco...

```
function new_state = calculateScores(car_id, current_data, old_state, resultsStore)

%% Preprocess and perform calculations
current_data = preprocessData(current_data);

%% Predict driving events
current_data = predictEvents(current_data);

%% Count events for each ten second window
countsByTime = countEvents(current_data);

%% Write discrete data to mongodb
updateResultsStore(car_id,countsByTime,resultsStore);

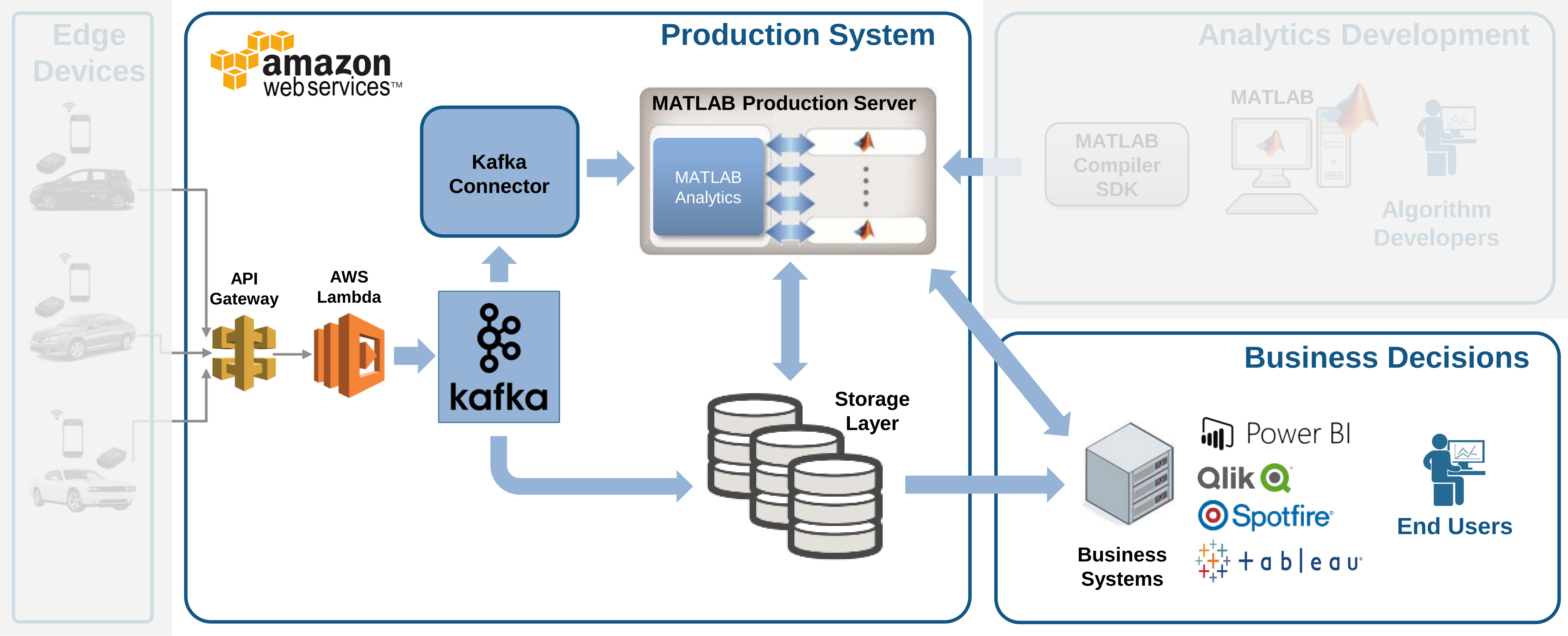
```

Name	Value
curDir	'/home/demou

```
>>
```

4 Integrate with Production Systems

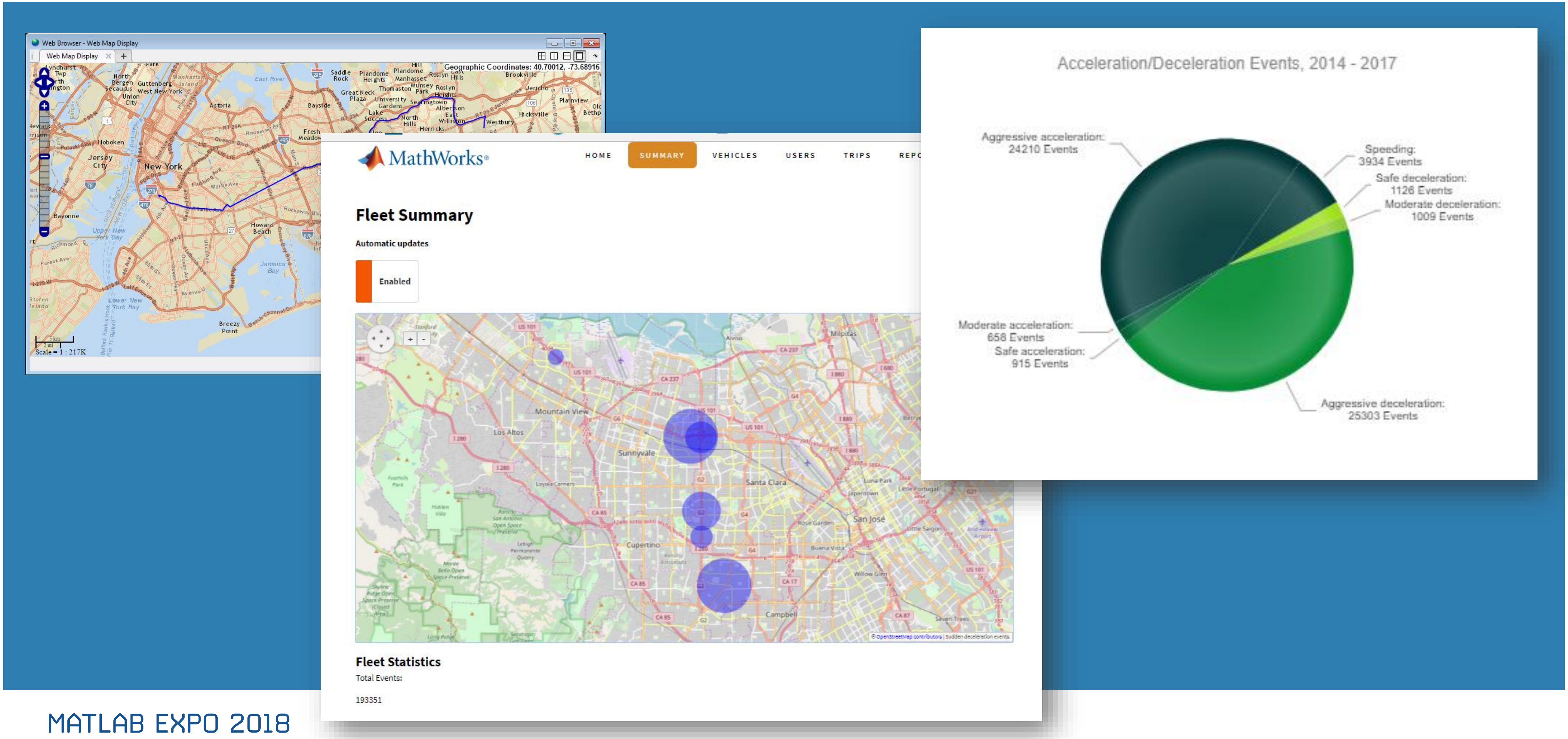
Tie in your Dashboard Application



5

Visualize Results

Complete Your Application



Web Browser - Web Map Display
Web Map Display
Geographic Coordinates: 40.70012, -73.68916
New York
Scale = 1 : 217K
MathWorks
HOME
SUMMARY
VEHICLES
USERS
TRIPS
REPO
Acceleration/Deceleration Events, 2014 - 2017
Aggressive acceleration: 24210 Events
Speeding: 3934 Events
Safe deceleration: 1126 Events
Moderate deceleration: 1009 Events
Moderate acceleration: 658 Events
Safe acceleration: 915 Events
Aggressive deceleration: 25303 Events

Fleet Summary

Automatic updates

Enabled

Fleet Statistics

Total Events:

193351

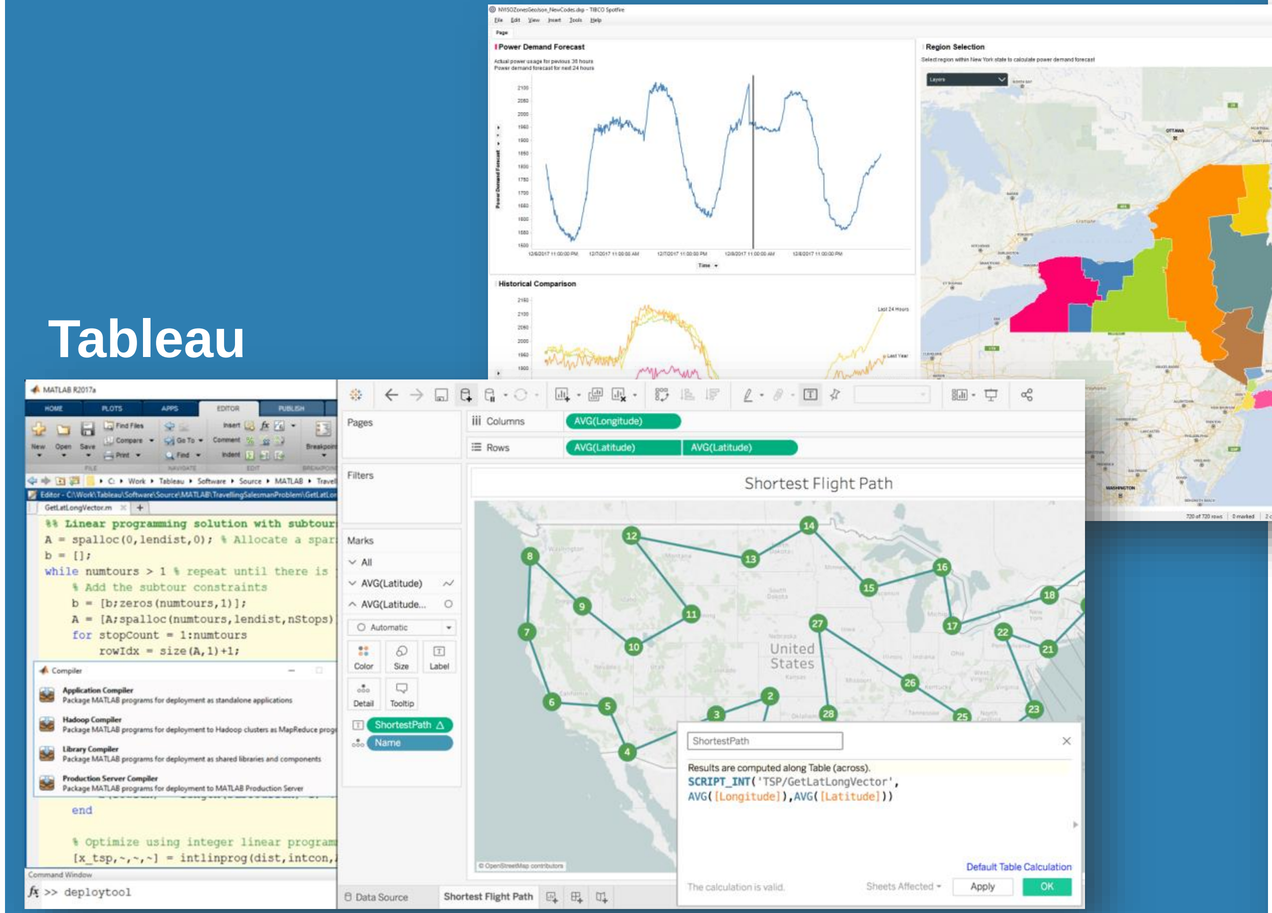
5

Visualize Results

Scalable Analytics with Enterprise BI Tools

TIBCO Spotfire

Tableau


Power Demand Forecast
Actual power usage for previous 36 hours
Power demand forecast for next 24 hours
Time
Historical Comparison
Last 24 Hours
Last Year
Region Selection
Select region within New York state to calculate power demand forecast
Layers
MATLAB R2017a
HOME
PLOTS
APPS
EDITOR
PUBLISH
Compare
Print
Go To
Find
Comment
Indent
New
Open
Save
Breakpoints
FILE
NAVIGATE
EDIT
C: ▸ Work ▸ Tableau ▸ Software ▸ Source ▸ MATLAB ▸ Travel
Editor - C:\Work\Tableau\Software\Source\MATLAB\TravellingSalesmanProblem\GetLatLon
GetLatLongVector.m
Compiler
Application Compiler
Package MATLAB programs for deployment as standalone applications
Hadoop Compiler
Package MATLAB programs for deployment to Hadoop clusters as MapReduce prog
Library Compiler
Package MATLAB programs for deployment as shared libraries and components
Production Server Compiler
Package MATLAB programs for deployment to MATLAB Production Server
Command Window
Pages
Filters
Marks
All
AVG(Latitude)
AVG(Latitude...
Automatic
Color
Size
Label
Detail
Tooltip
ShortestPath
Name
Columns
AVG(Longitude)
Rows
AVG(Latitude)
AVG(Latitude)
Shortest Flight Path
United States
Data Source
Shortest Flight Path
ShortestPath
Default Table Calculation
The calculation is valid.
Sheets Affected
Apply
OK

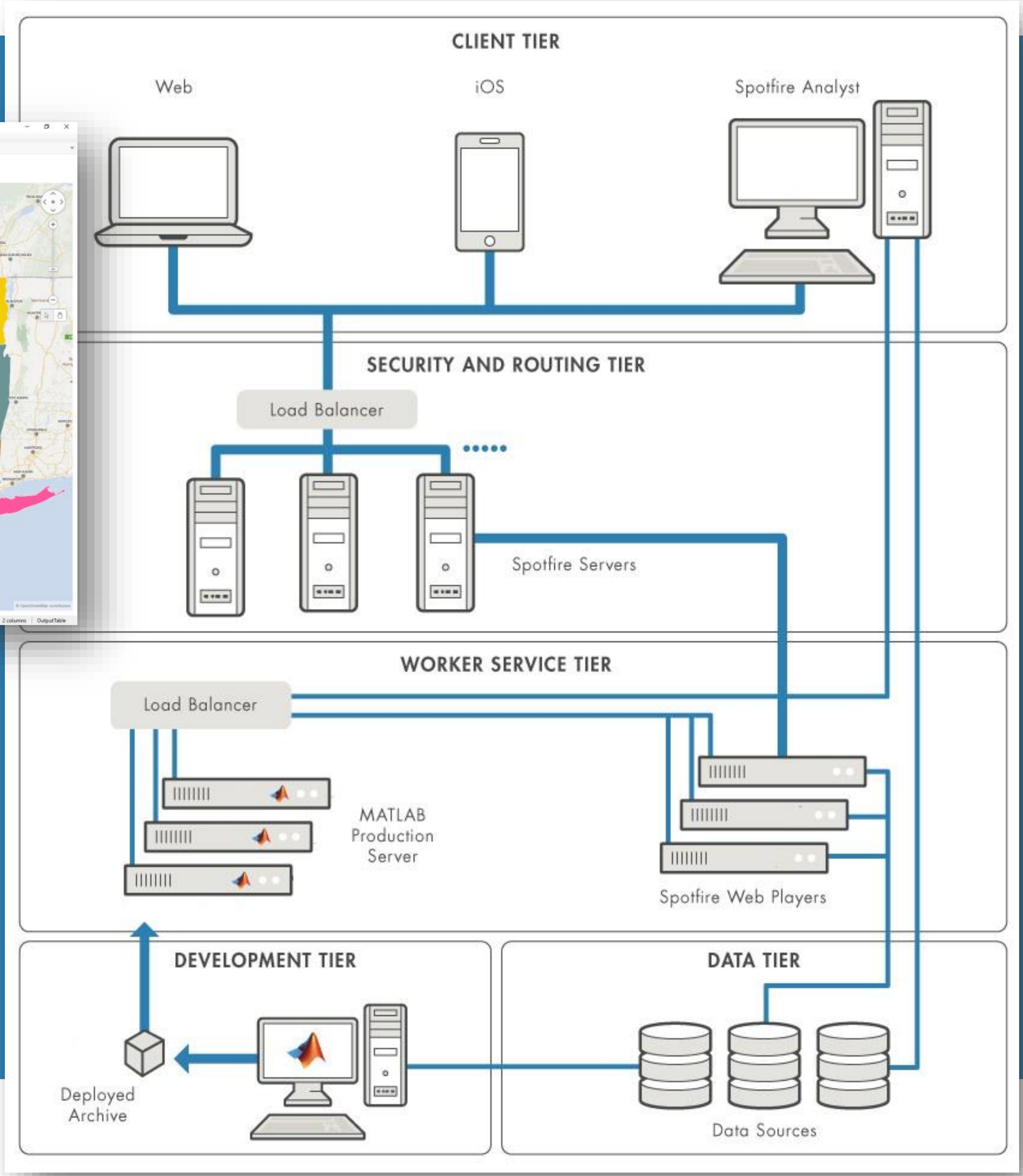
```
%% Linear programming solution with subtour
A = spalloc(0,lendist,0); % Allocate a spar
b = [];
while numtours > 1 % repeat until there is
    % Add the subtour constraints
    b = [b;zeros(numtours,1)];
    A = [A;spalloc(numtours,lendist,nStops)
    for stopCount = 1:numtours
        rowIdx = size(A,1)+1;
    end

    % Optimize using integer linear program
    [x_tsp,~,~,~] = intlinprog(dist,intcon,
```

```
>> deploytool
```

Results are computed along Table (across).

```
SCRIPT_INT('TSP/GetLatLongVector',
AVG([Longitude]),AVG([Latitude]))
```


CLIENT TIER

Web

iOS

Spotfire Analyst

SECURITY AND ROUTING TIER

Load Balancer

Spotfire Servers

WORKER SERVICE TIER

Load Balancer

MATLAB Production Server

Spotfire Web Players

DEVELOPMENT TIER

Deployed Archive

DATA TIER

Data Sources

Key Takeaways

- MATLAB connects directly to your data so you can quickly design and validate algorithms

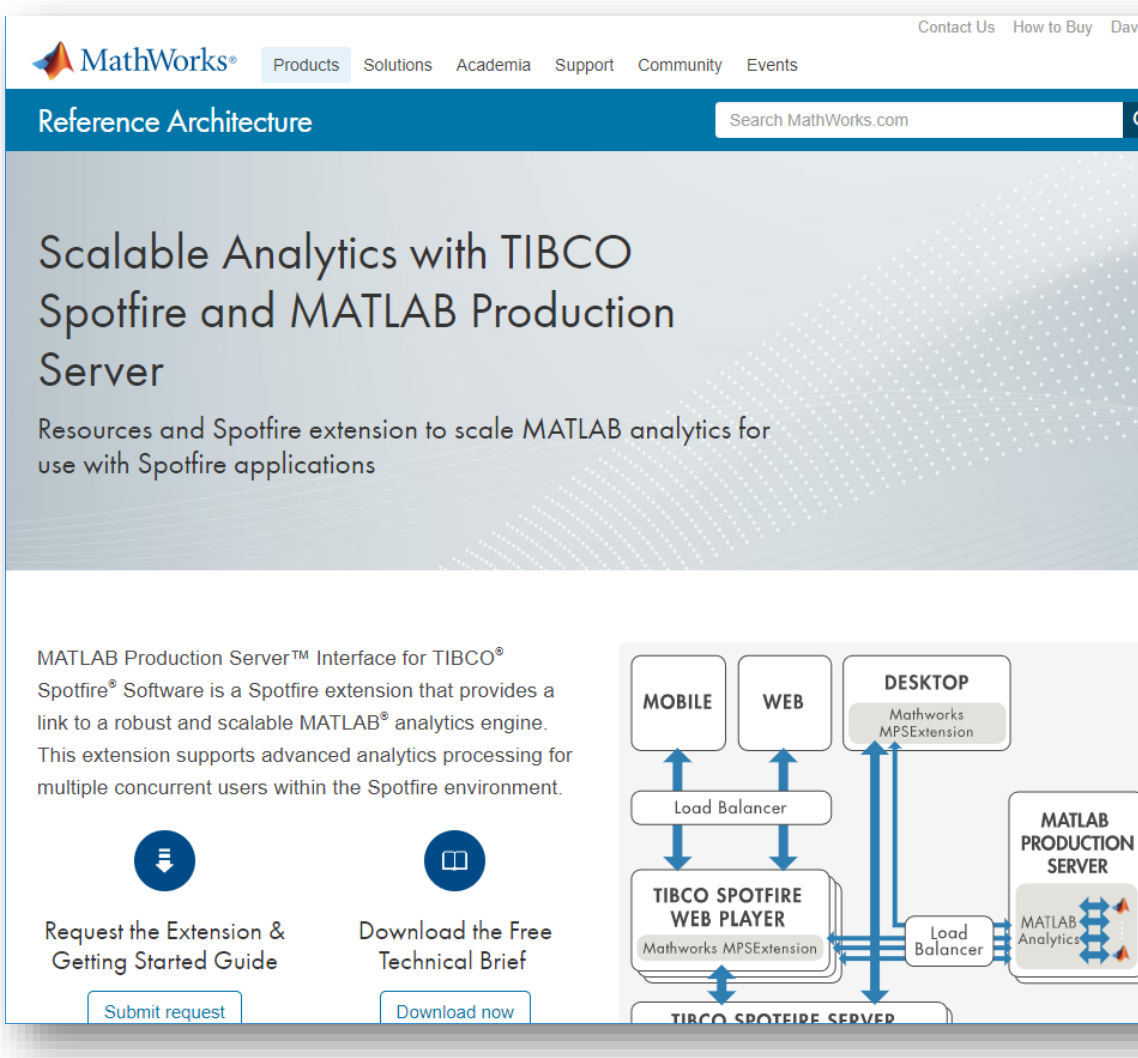
- The MATLAB language and apps enable fast design iterations

- 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



Scalable Analytics with TIBCO Spotfire and MATLAB Production Server

Resources and Spotfire extension to scale MATLAB analytics for use with Spotfire applications

MATLAB Production Server™ Interface for TIBCO® Spotfire® Software is a Spotfire extension that provides a link to a robust and scalable MATLAB® analytics engine. This extension supports advanced analytics processing for multiple concurrent users within the Spotfire environment.

Request the Extension & Getting Started Guide

Download the Free Technical Brief