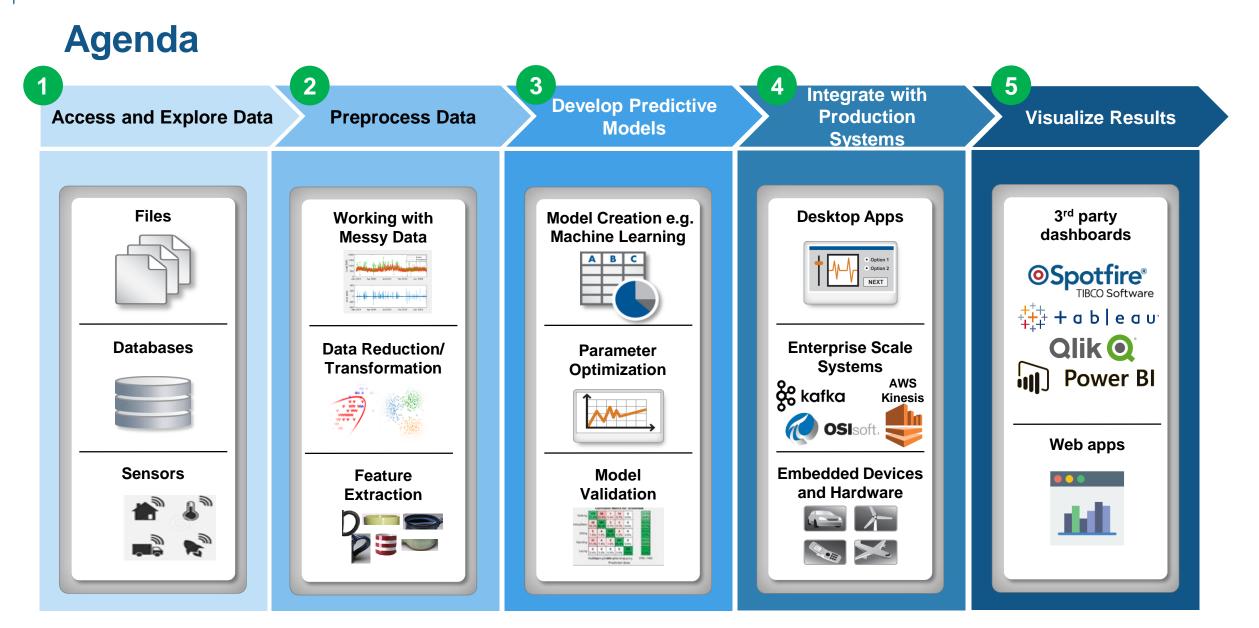
MATLAB EXPO 2018

Ampliando MATLAB Analytics con Kafka y Servicios en la Nube

Lucas García

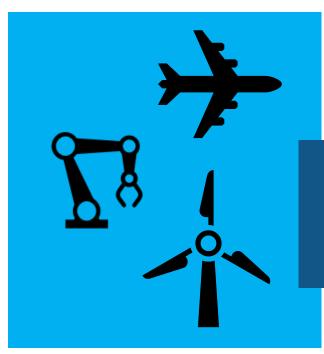








The Need for Large-Scale Streaming



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

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

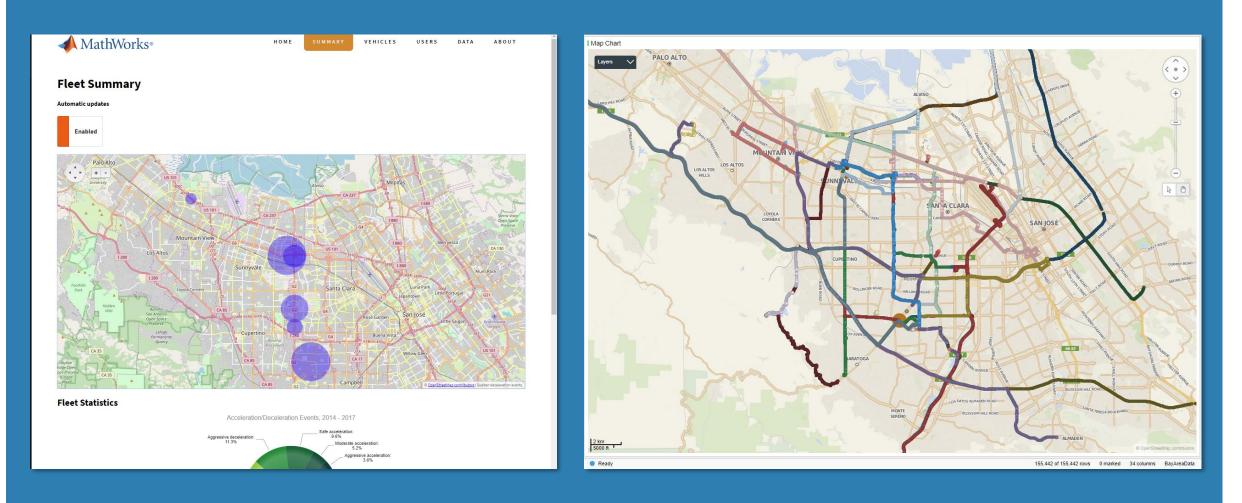
Example Problem – How's my driving?

- 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



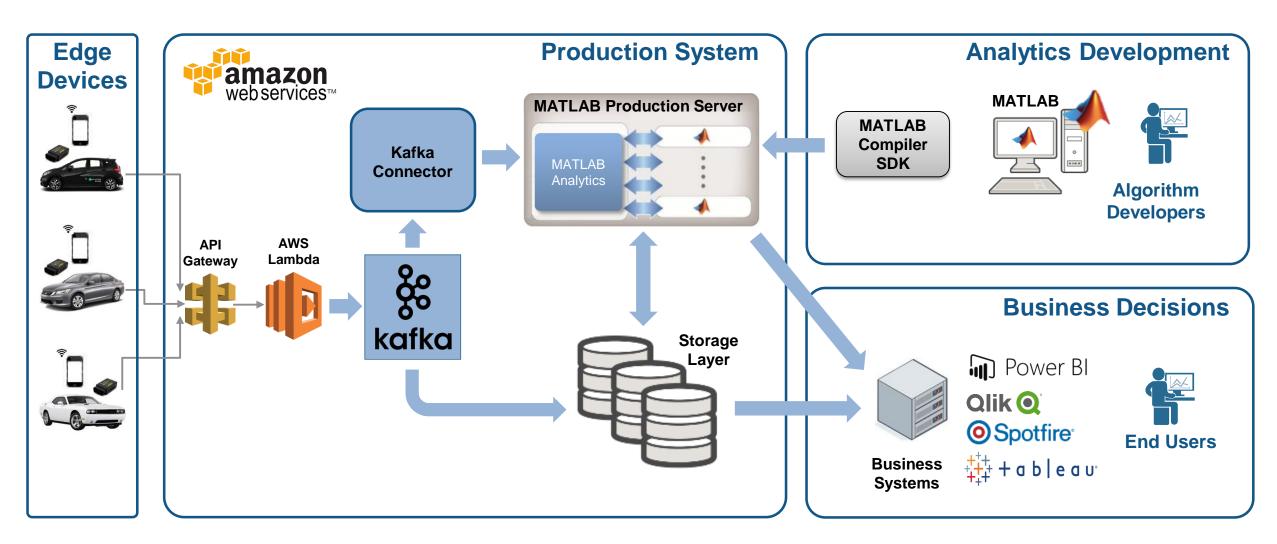


Example: Fleet Analytics with MATLAB





Fleet Analytics Architecture

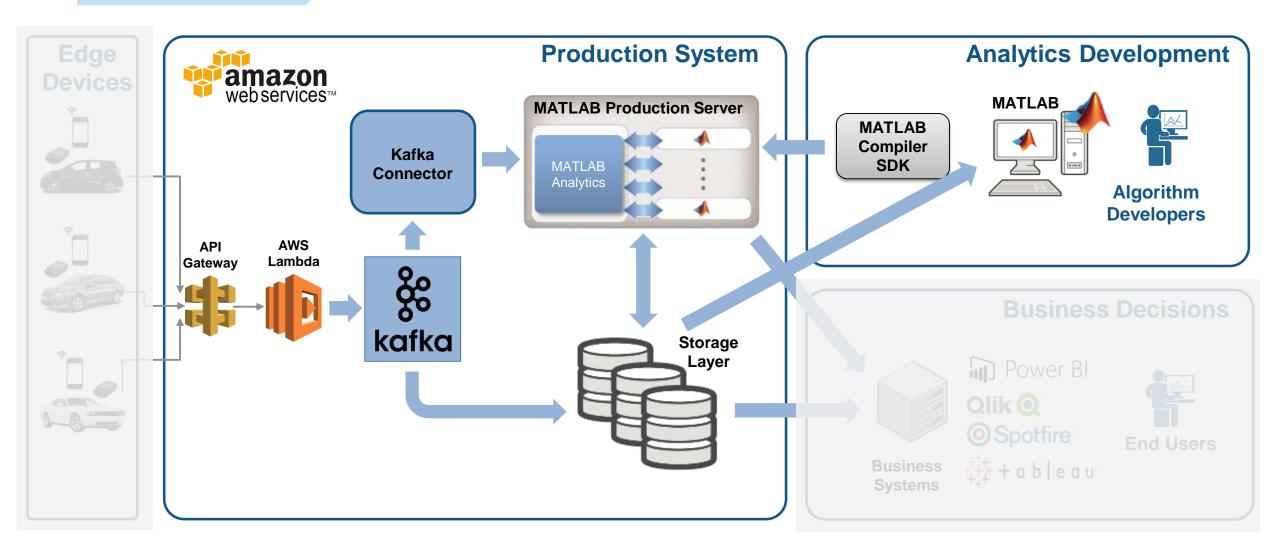


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Access and Explore Data

1

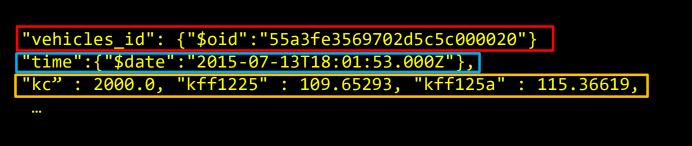
The first step is to clean up the incoming data



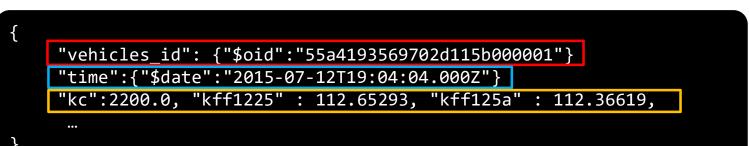
Access and Explore Data The Data: Timestamped messages with JSON encoding











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Access and Explore Data Access a Sample of Data

Raw Data

1

✓ Decode JSON data✓ Create Timetable

		1	2
	timestamp	value	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'

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	59.04
2 Sun Jul 12 16:18:42 UTC 2015	55a3fe356	55a3fe356	17.1000	-84.9322	45.4704	NaN	NaN	NaN	NaN	57.86
3 Sun Jul 12 16:18:43 UTC 2015	55a3fe356	55a3fe356	18.9000	-84.9322	45.4705	NaN	NaN	NaN	NaN	52.7
4 Sun Jul 12 16:18:44 UTC 2015	55a3fe356	55a3fe356	18.9000	-84.9322	45.4705	NaN	NaN	NaN	NaN	51.1
5 Sun Jul 12 16:18:45 UTC 2015	55a3fe356	55a3fe356	18.0000	-84.9321	45.4706	NaN	NaN	NaN	NaN	49.1
6 Sun Jul 12 16:19:13 UTC 2015	55a3fe356	55a3fe356	58.5000	-84.9305	45.4686	NaN	NaN	NaN	NaN	73.2
7 Sun Jul 12 16:19:14 UTC 2015	55a3fe356	55a3fe356	56.7000	-84.9304	45.4685	NaN	NaN	NaN	NaN	75.3
8 Sun Jul 12 16:19:15 UTC 2015	55a3fe356	55a3fe356	57.6000	-84.9304	45.4683	NaN	NaN	NaN	NaN	70.7
9 Sun Jul 12 16:19:16 UTC 2015	55a3fe356	55a3fe356	56.7000	-84.9303	45.4682	NaN	NaN	NaN	NaN	62.8



Preprocess Data

Develop a Preprocessing Function

Timetable

2

	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	NoN	NoN	NoN	NoN	72 2005
7 Sun Jul 12 16:19:14 UTC 2015	55a3fe356	55a3fe356	56.7000	-84.9304	45.46	Preproce	ess data			
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	45.46	t = sor	trows(t)			

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

✓ Clean up ✓ Enrich ✓ Restructure

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



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1

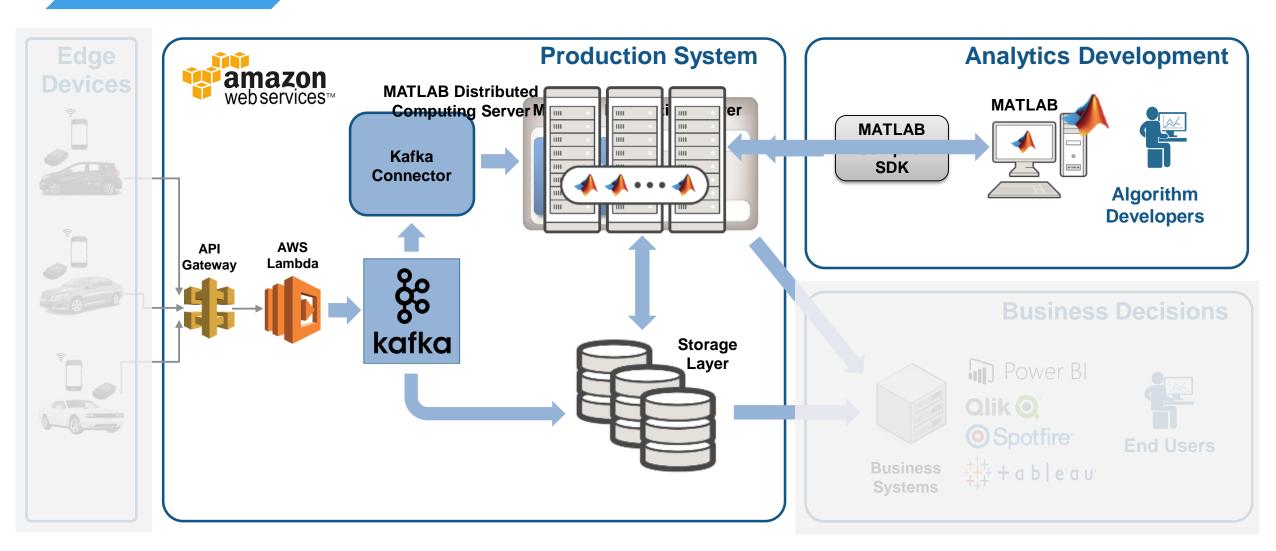
Access and Explore Data



Develop Predictive Models

3

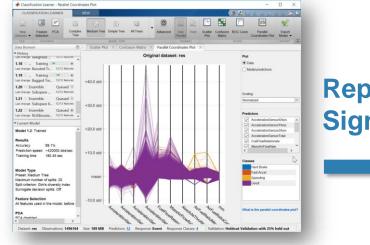
Develop a Predictive Model



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

	1	2	3	4	5
time	Event Sp	peedGPS	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 ast /	Accel	37.7640	0.1527	0.4666	0.857
Sun May 03 21:00:42 UTC 2015 ast /	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-EE LITC 201E Lord	Draka	22 4000	0.2059	0.0054	0.906

Label Events



Represent Signals

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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');

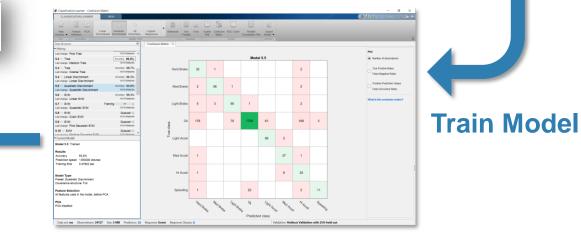
Scale Up

3

Develop Predictive Models

Scale to out of memory data

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



Validate Model



Develop Predictive Models

3

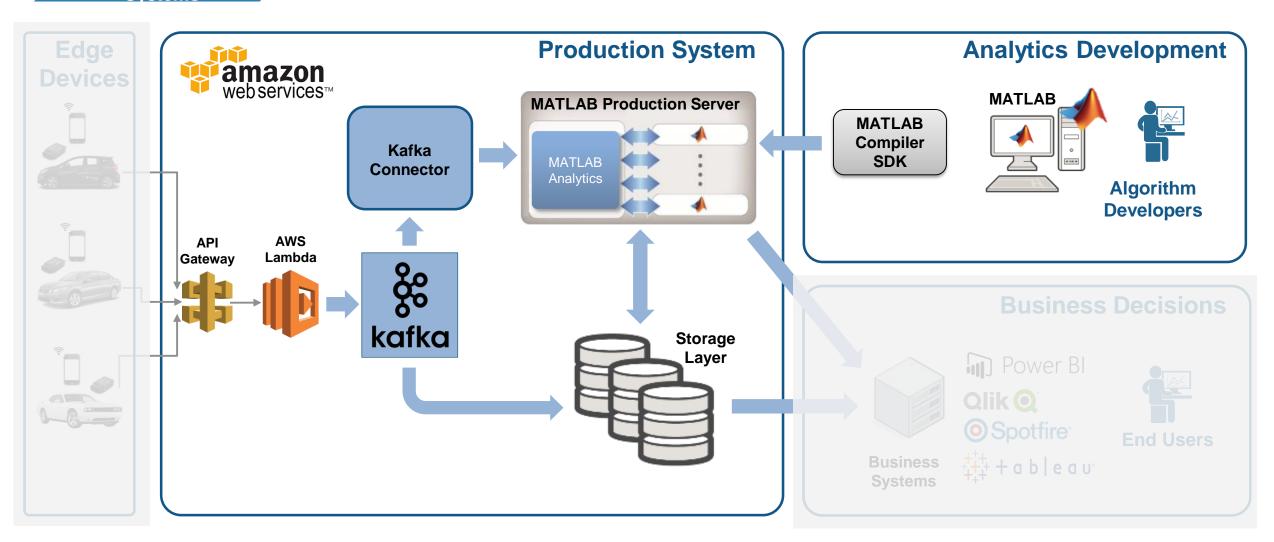
Develop a Predictive Model in MATLAB

📣 Classifica	ition Learner														- 0	\times
CLASS	IFICATION LEARNER	VIEW	V.									3111	88888	🛛 📣 🖪	4 Li 9 C	2 🗖 🖓
4		-Ja	2			0				1		Ľ				
New Session 👻		All Quick-To- Train		All Linear	Fine Tree	Advanced	Parallel	Scatter Plot	Confusion Matrix		Parallel Coordinates Plot	Export Model 🕶				_
FILE	FEATURES			MODEL TYPE			TRAINING			PLOTS		EXPORT				
Data Brows	er			0												
 History 	N			-												
	5															
- Current M	odel															



4

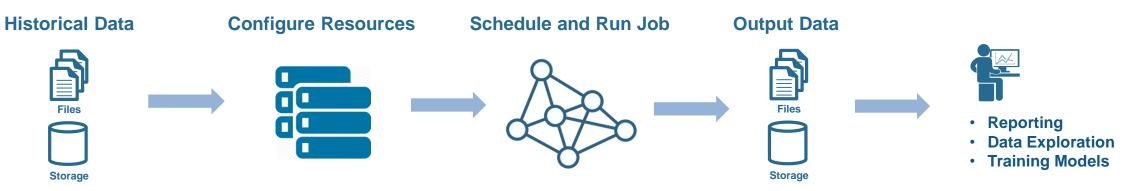
Integrate Analytics with Production Systems



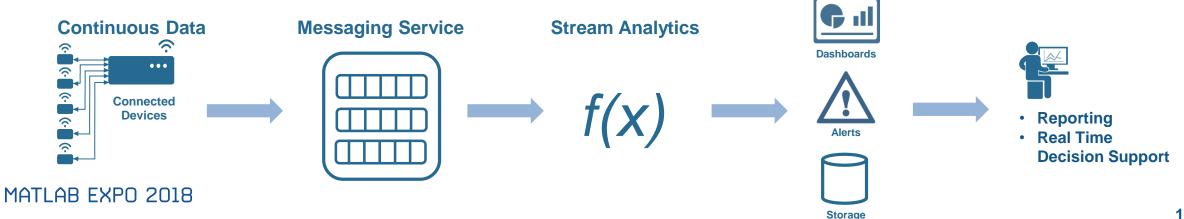


A quick Intro to Stream Processing

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



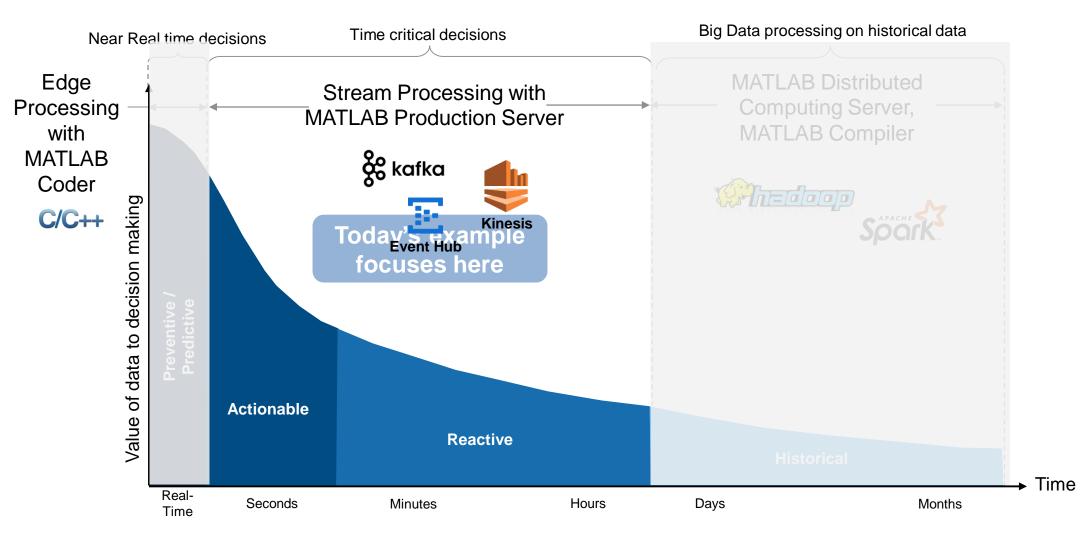
Stream Processing applies computation to an unbounded data set that is produced continuously





4

Why stream processing?





4

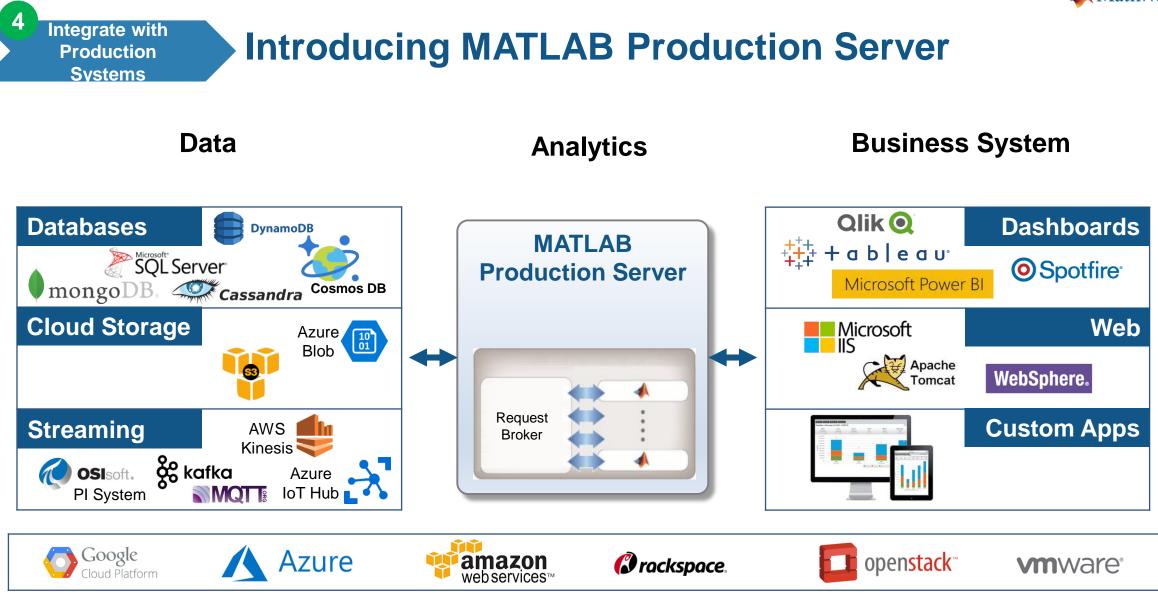
Streaming data is treated as an unbounded Timetable

RPM Torque Vehicle Fuel **Event** Time 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 110 113 110 18:30:50 55a3fe 2000 100

Input Table

State		Outp	out Table	
	Time wind	ow	Vehicle	Score
Function				
+	18:00:00	18:10:00	55a3fd	5
State			55a3fe	
			55a419	
MATLAB	18:10:00	18:20:00	55a3fd	7
Function			55a3fe	3
Function			55a419	
	18:20:00	18:30:00	55a3fd	
State			55a3fe	4
			55a419	
	18:30:00	18:40:00	55a3fd	
Function			55a3fe	5
			55a419	8
State				

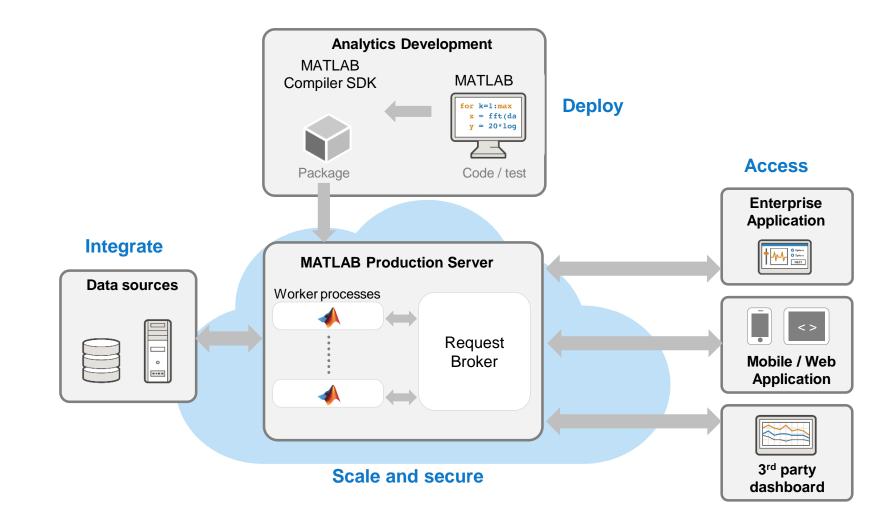




Platform



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



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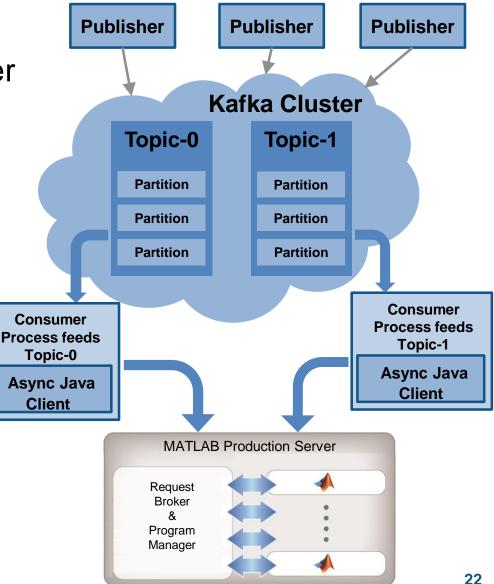
Integrate with

Production Systems

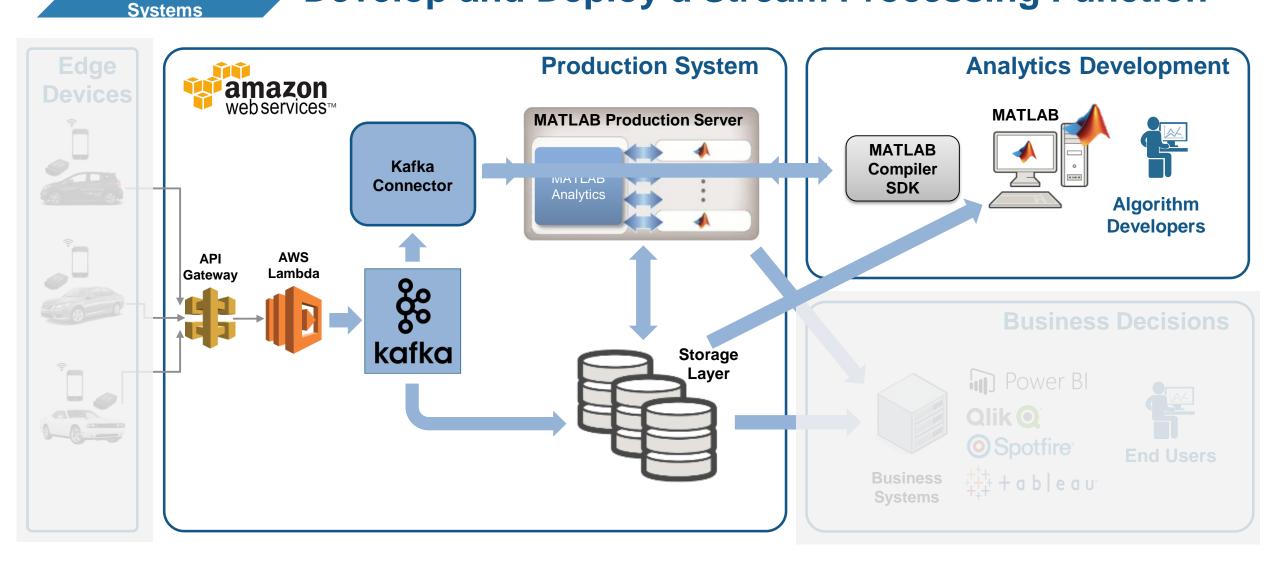


Connecting MATLAB Production Server to Kafka

- 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



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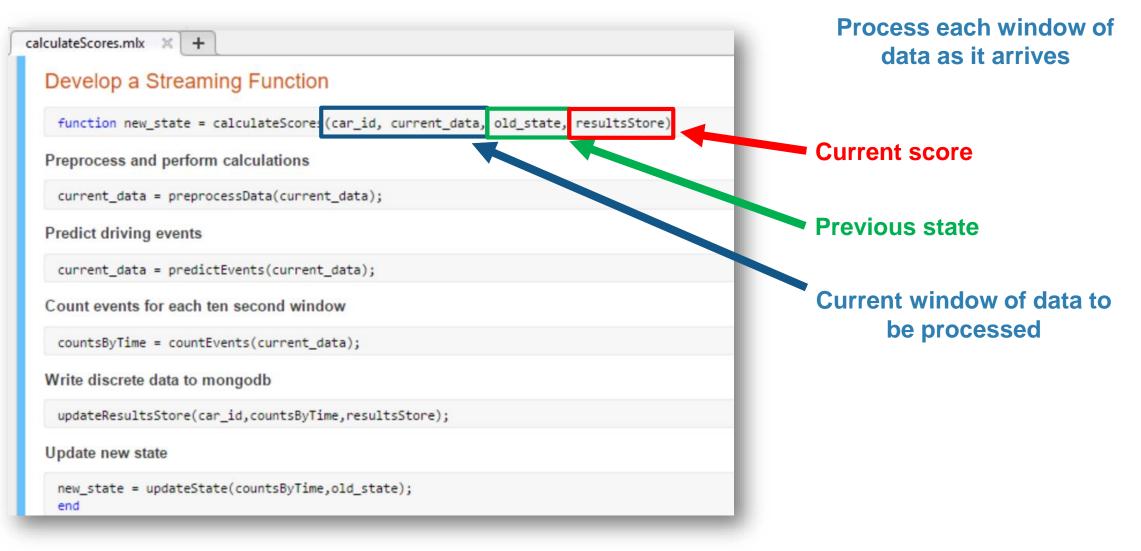
Integrate with

Production

MathWorks[®]



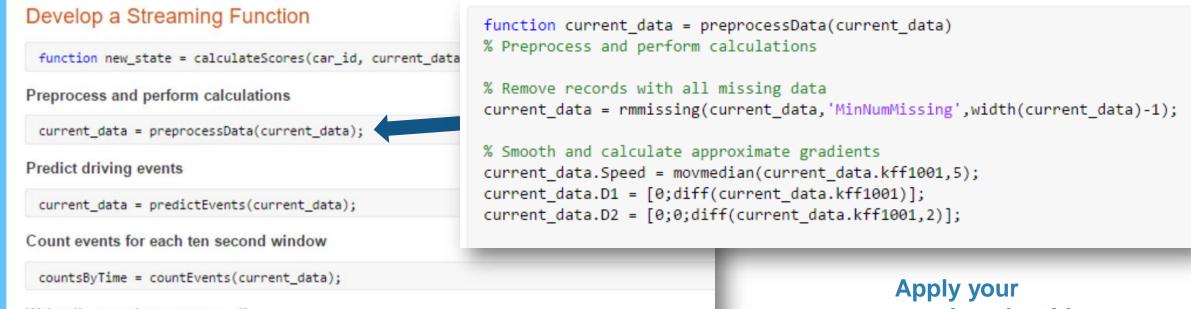
Develop a Stream Processing Function in MATLAB





Develop a Stream Processing Function in MATLAB

calculateScores.mlx 💥 🕂



Write discrete data to mongodb

updateResultsStore(car_id,countsByTime,resultsStore);

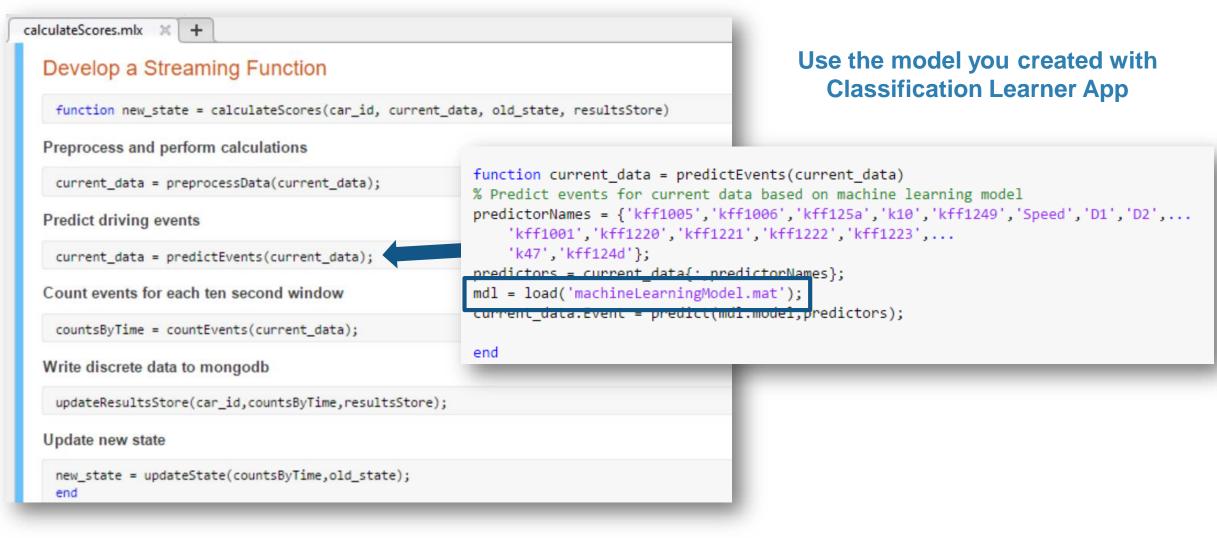
Update new state

new_state = updateState(countsByTime,old_state); end

pre-processing algorithm



Develop a Stream Processing Function in MATLAB

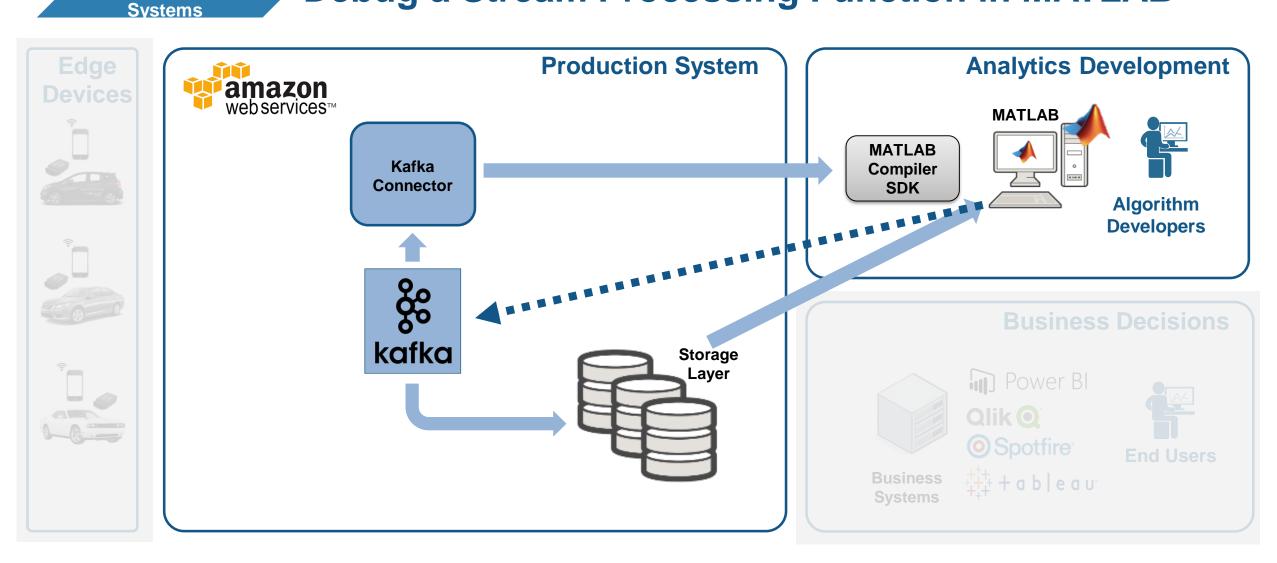




Develop a Stream Processing Function in MATLAB

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 Update Mongo database countsByTime = countEvents(current data); **Count of events by type and location** Write discrete data to mongodb **Results of driver scoring** updateResultsStore(car_id,countsByTime,resultsStore); Update new state new_state = updateState(countsByTime,old_state); end

Debug a Stream Processing Function in MATLAB



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4

Integrate with

Production

MathWorks[®]



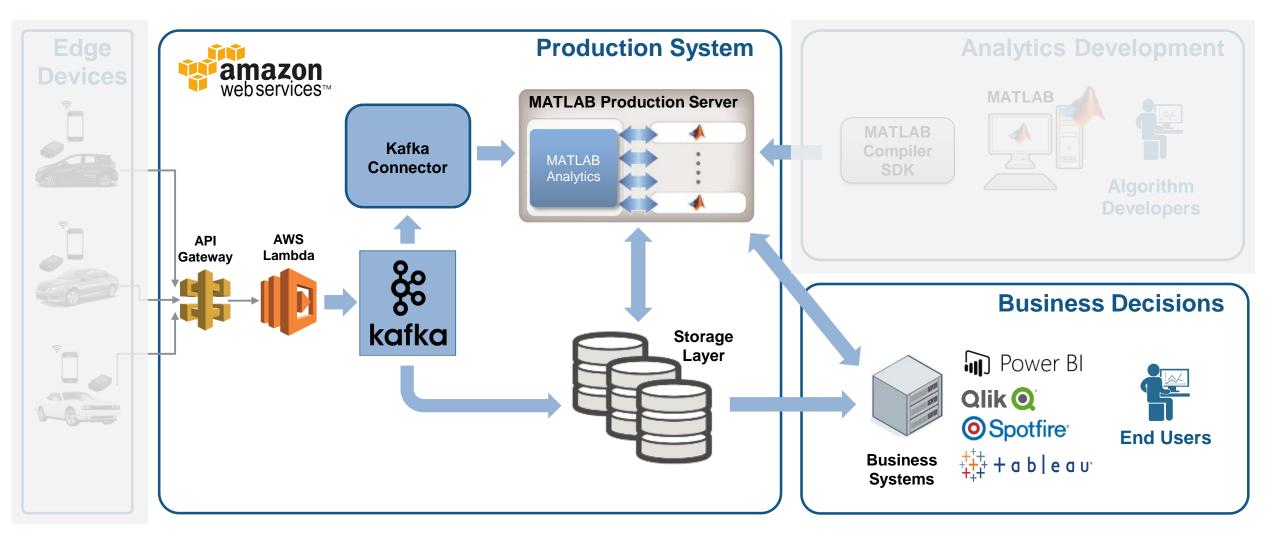
4

Debug a Stream Processing Function in MATLAB



4

Tie in your Dashboard Application

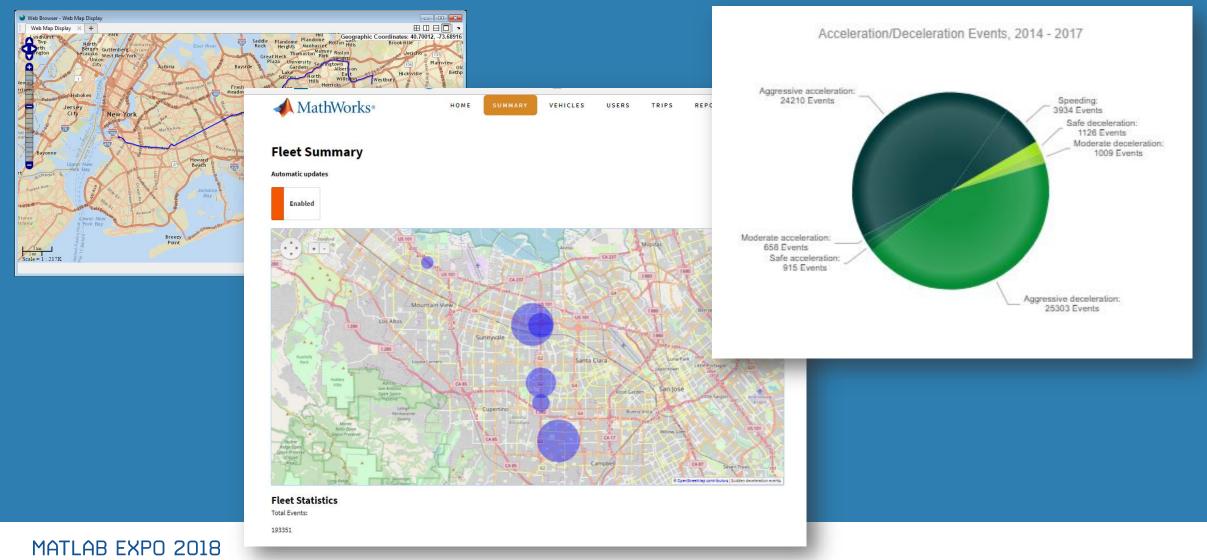




Visualize Results

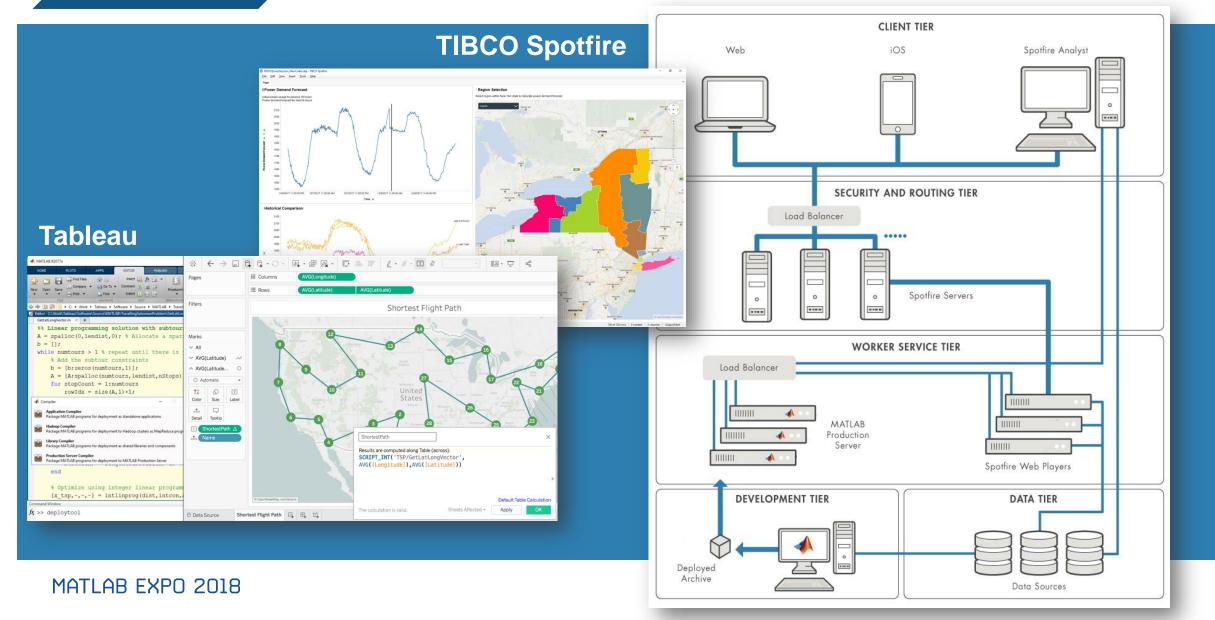
5

Complete Your Application





Scalable Analytics with Enterprise BI Tools



5

Visualize Results

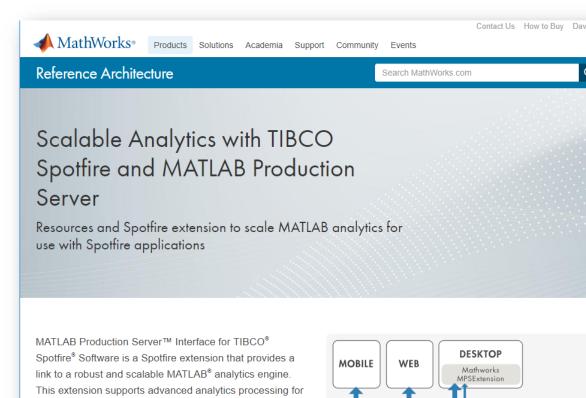
Key Takeaways

- 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
- <u>Statistics and Machine Learning Toolbox</u>
- Database Toolbox
- Mapping Toolbox
- MATLAB with TIBCO Spotfire
- MATLAB with Tableau
- MATLAB with MongoDB





MATLAB PRODUCTION

SERVER

Load Balancer