

Pivotal

A NEW PLATFORM FOR A NEW ERA

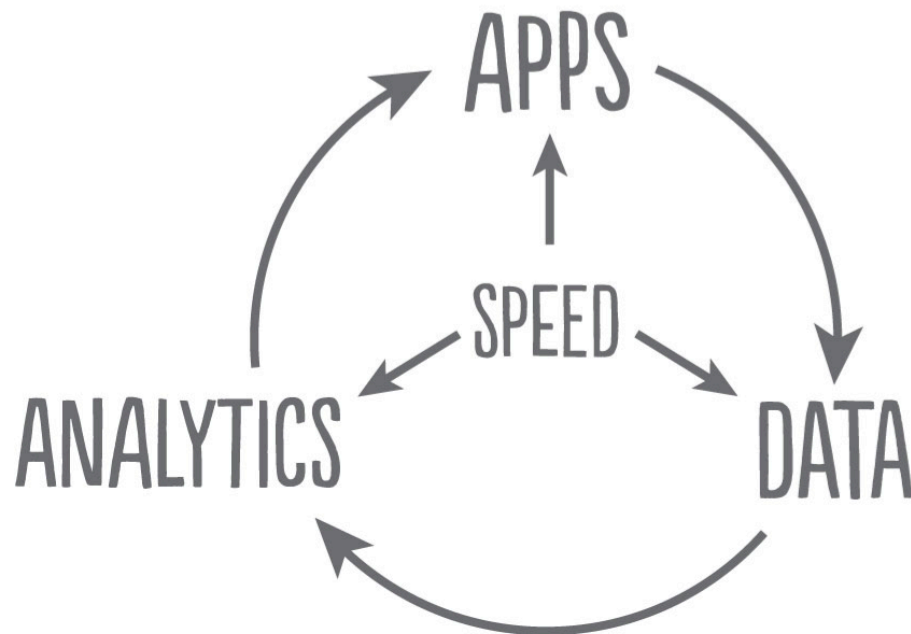
Driving the Future of Smart Cities How to Beat the Traffic

Strata Santa Clara – February 13, 2013

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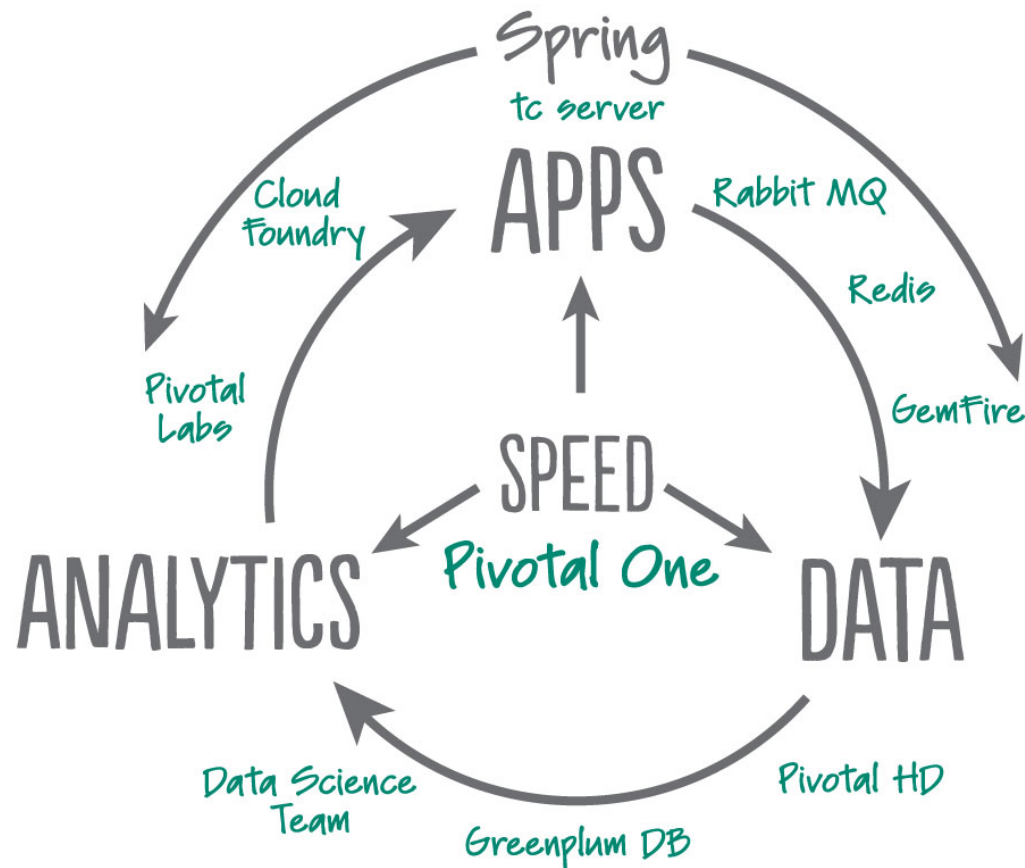
What Matters: Apps. Data. Analytics.

- ☑ *Apps power businesses, and those apps generate data*
- ☑ *Analytic insights from that data drive new app functionality, which in-turn drives new data*
- ☑ *The faster you can move around that cycle, the faster you learn, innovate & pull away from the competition*

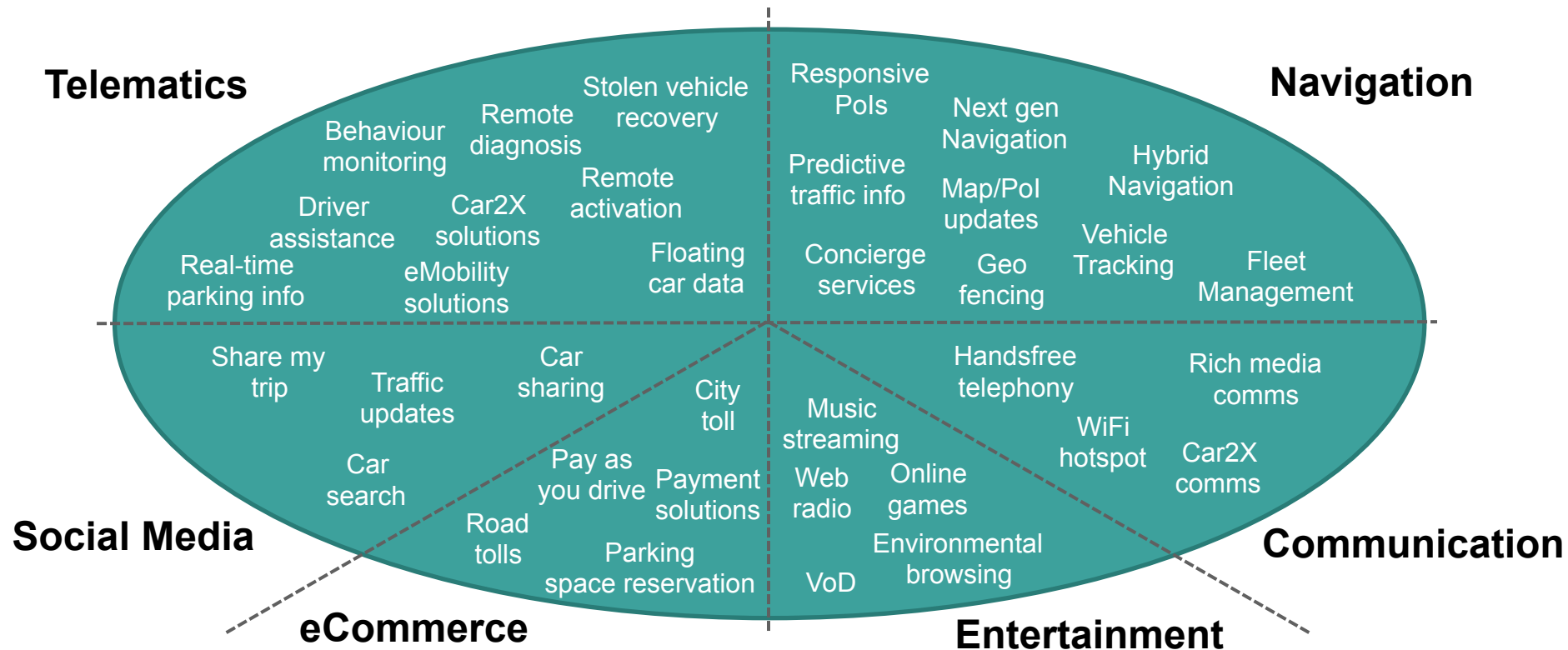


Pivotal's Opportunity

- ☑ *Uniquely positioned to help enterprises modernize each facet of this cycle today*
- ☑ *Comprehensive portfolio of products spanning Apps, Data & Analytics*
- ☑ *Converging these technologies into a coherent, next-gen Enterprise PaaS platform*

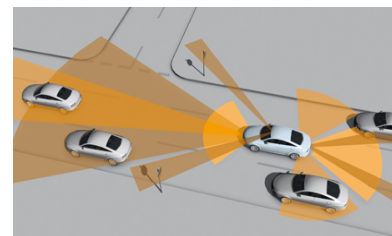
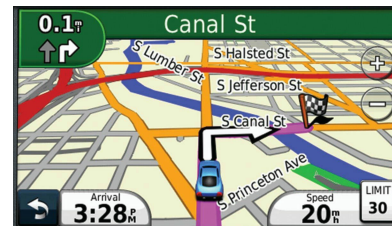


The Connected Car Drives Innovation



Possible Data Science Use-Cases

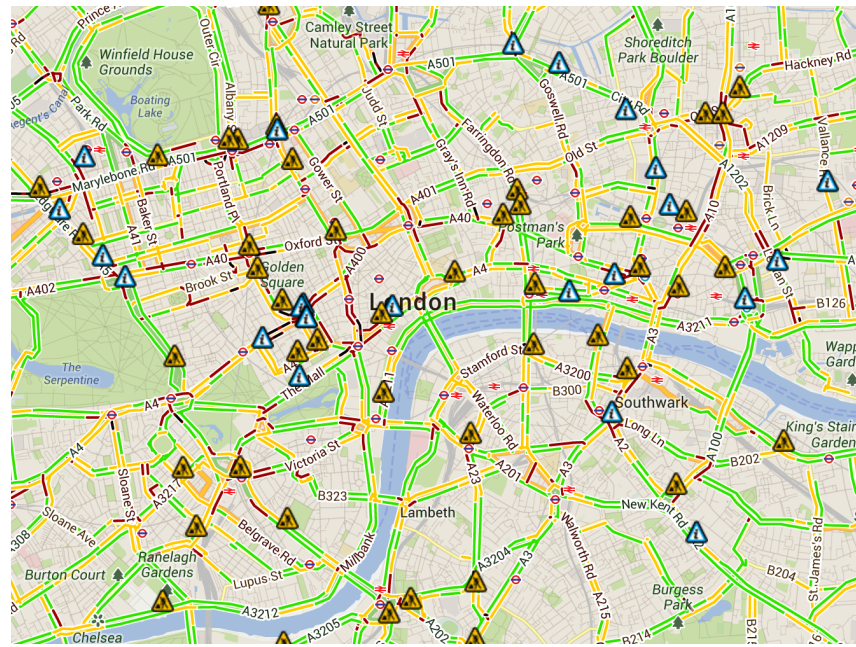
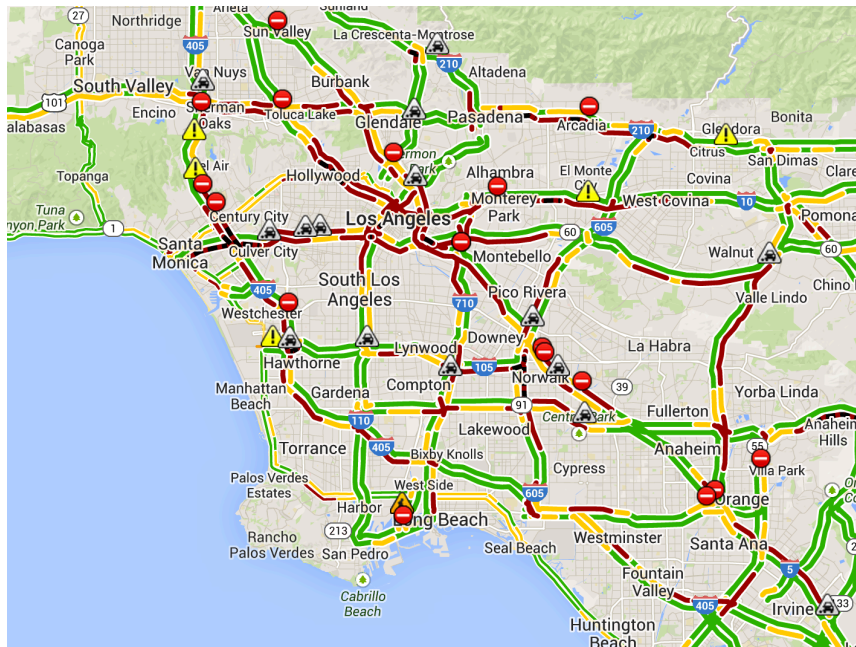
- **Predictive Car Maintenance**
 - More accurately predict part failure
 - Optimize part repair and replacement schedule
- **Leveraging Driving Behavior**
 - Useful to differentiate insurance pricing based on driving style
 - Optimize car design
- **Improving GPS Systems**
 - Establish baseline for traffic congestion
 - Gain a detailed view on traffic
 - Create more meaningful metrics for routing
- **Predictive Power for Assistance Systems**
 - Optimize fuel efficiency
 - Predict the future state of a car in the next 2 minutes (starts, stops, emergency braking)
- **Traffic Light Assistance**
 - Signal timing of traffic lights
 - Crowd sourcing of traffic signals



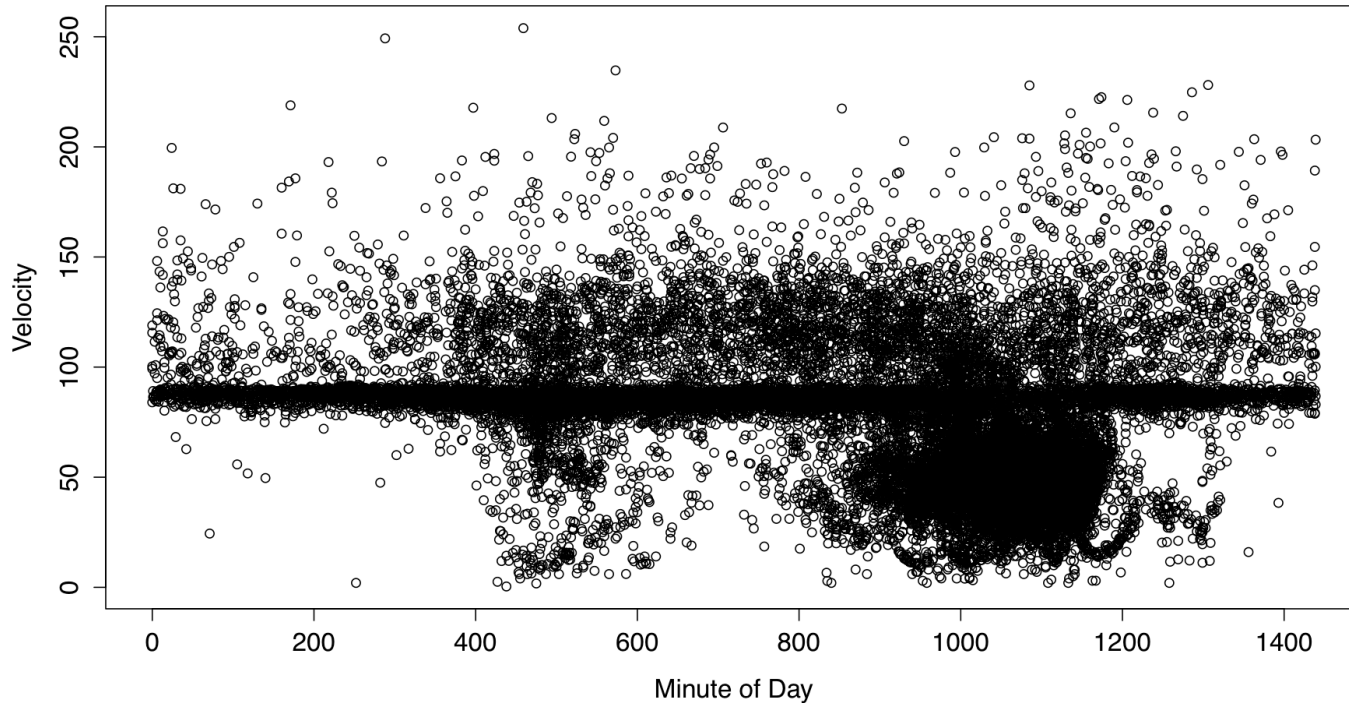
An aerial photograph of a multi-lane highway filled with cars, illustrating the concept of traffic data. The highway is viewed from an elevated angle, showing multiple lanes of traffic moving in both directions. The surrounding area includes green hills, some buildings, and a road that branches off to the right. The text "What does traffic data look like?" is overlaid in white on the right side of the image.

**What does
traffic data
look like?**

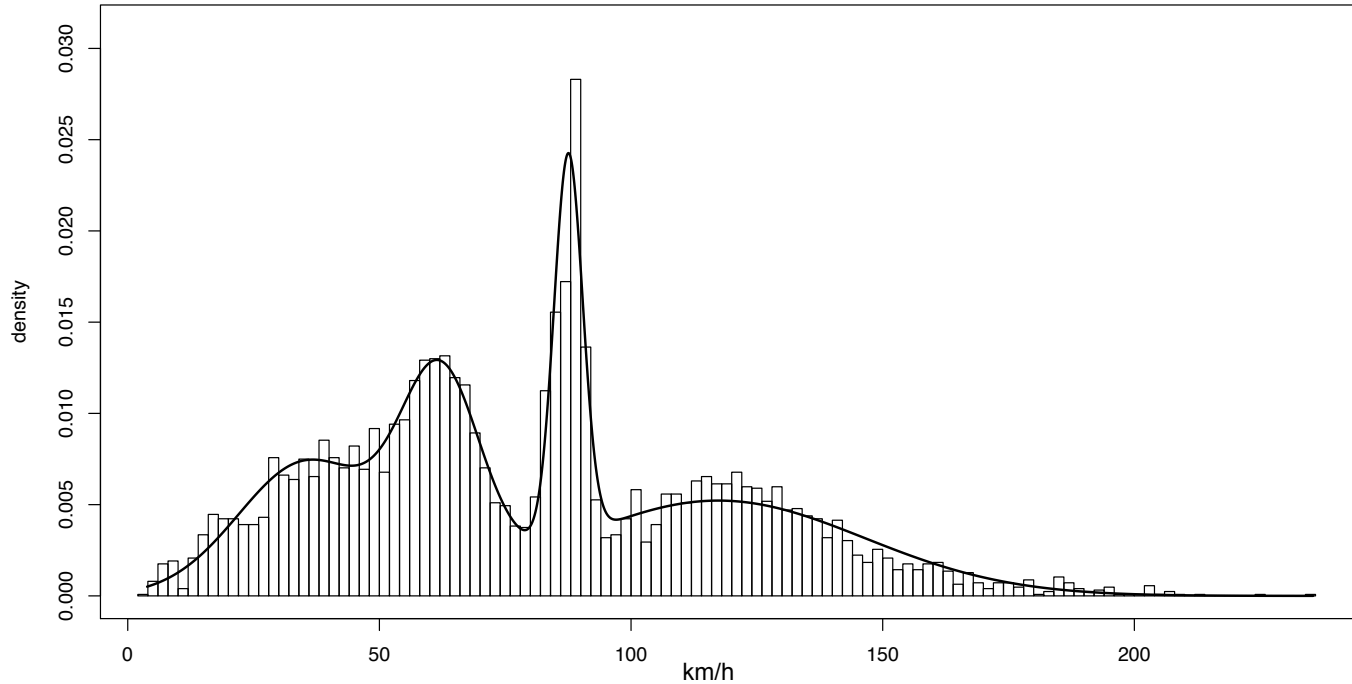
...like this?



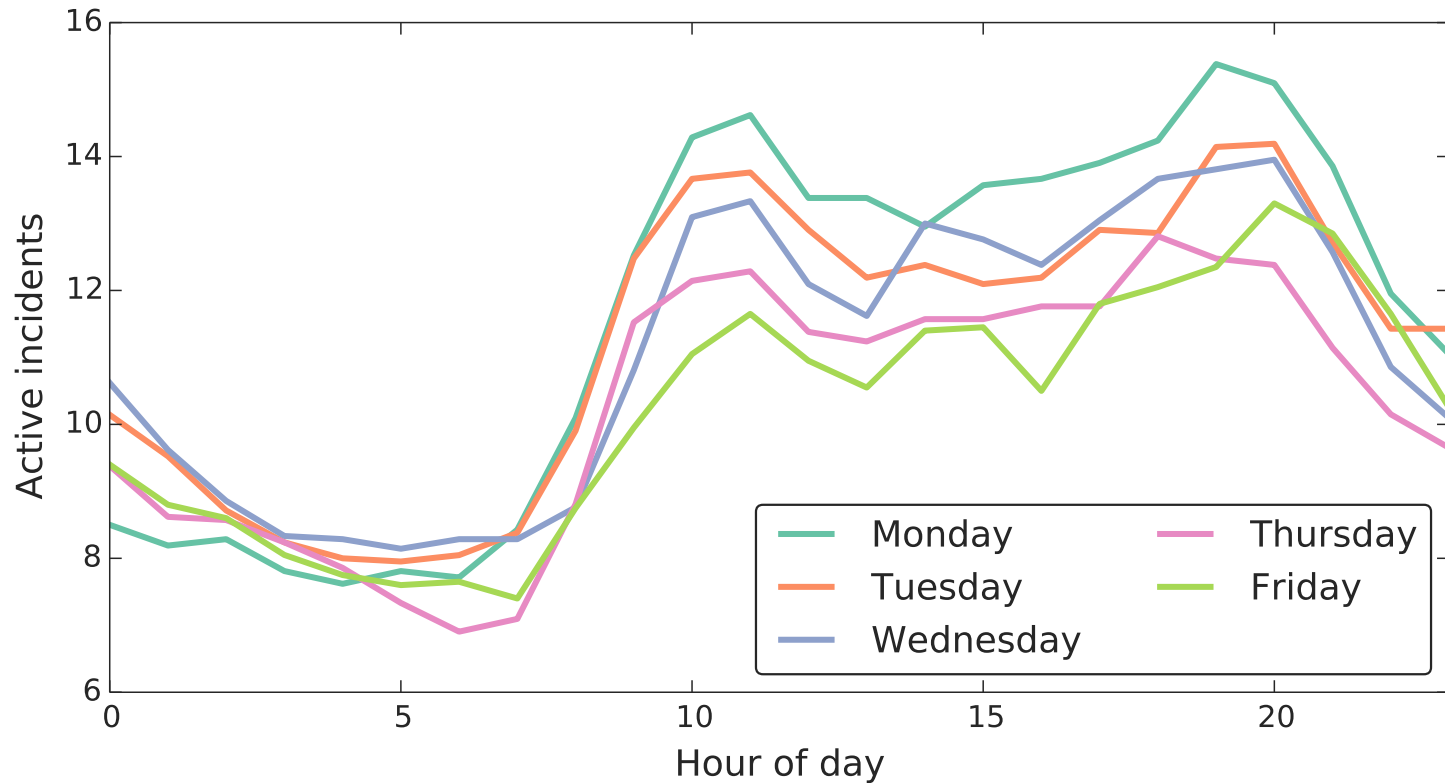
How fast are vehicles moving?



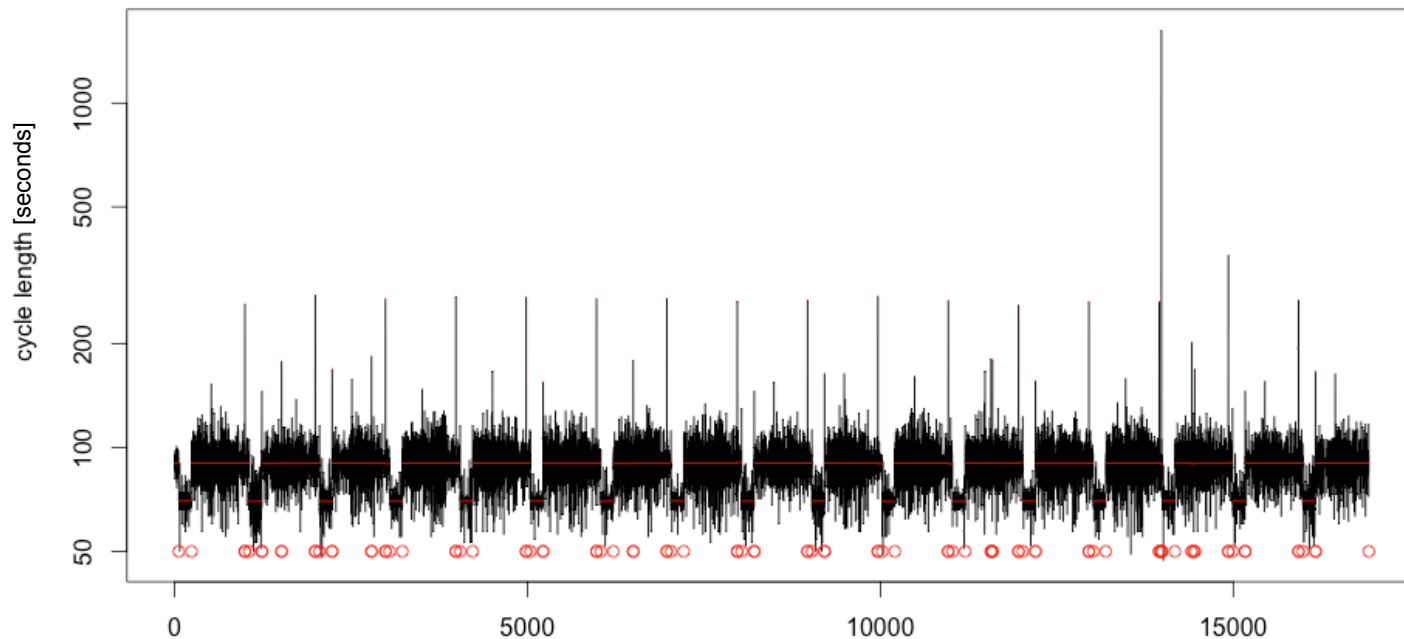
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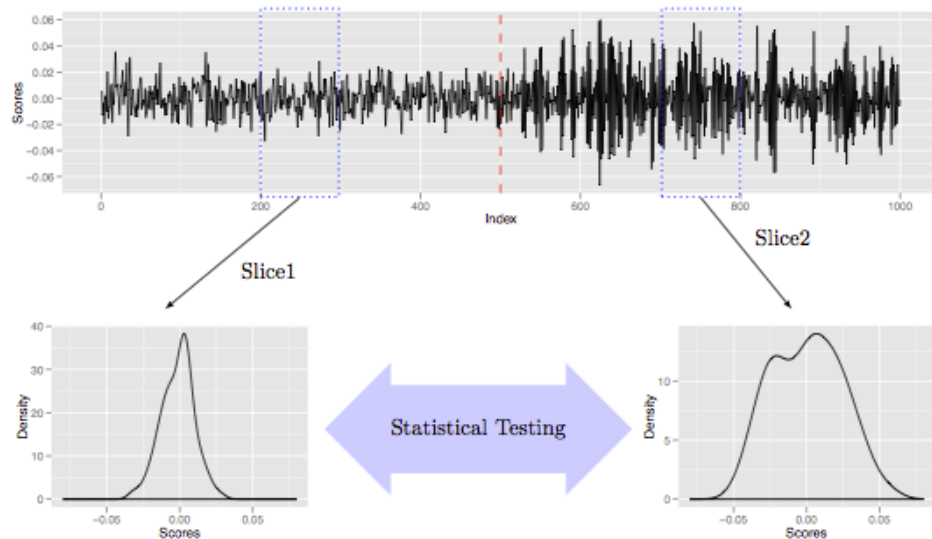
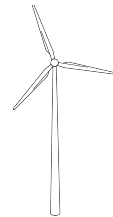
When do disruptions happen?



When will the light change?



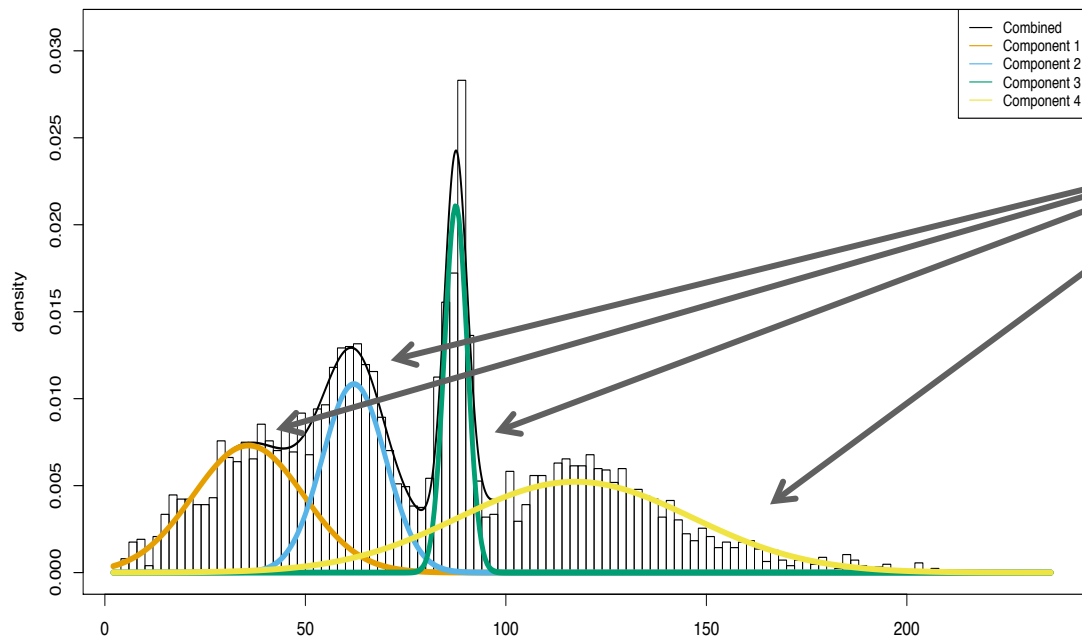
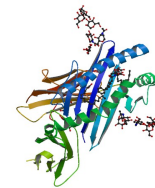
Taking Lessons From Other Disciplines



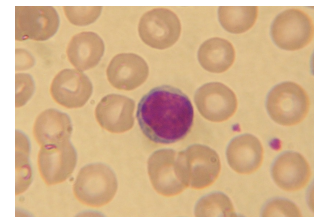
Change-Point Detection can be used to uncover **regimes in wind-turbine data**.

It can also be applied to uncover **regimes in traffic light switching patterns**.

Taking Lessons From Other Disciplines



Different **Cell**
Populations



Different **Driving**
Conditions



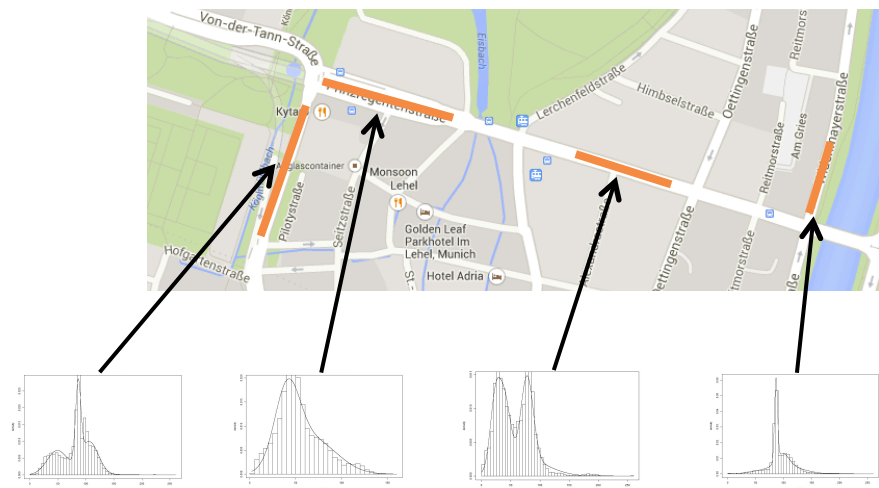
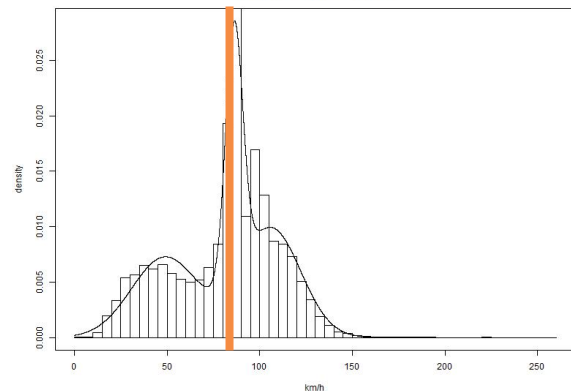
Understanding Traffic Flow

A dynamic, more detailed understanding of traffic is now possible.

Can we answer both *‘What velocity?’* and *‘Why?’*

Context

- Current GPS systems are based on average velocity over street segments
- Real-time traffic information (e.g. Waze) does not deliver detailed view nor prediction

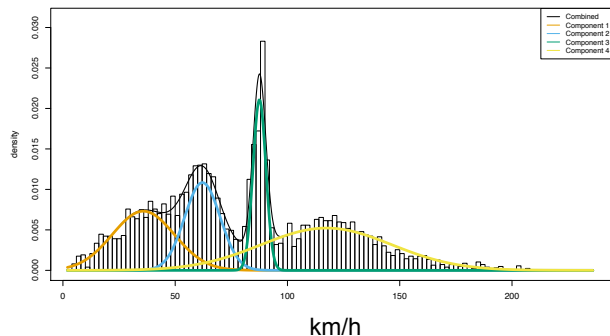


Our Approach – Multi-step algorithm

From our experience, **real-world data** often requires **multi-step procedures**

Step 1: Answer ‘What velocity?’

First find **distinct velocity groups**



Step 2: Answer ‘Why?’

Find **influencing effects**



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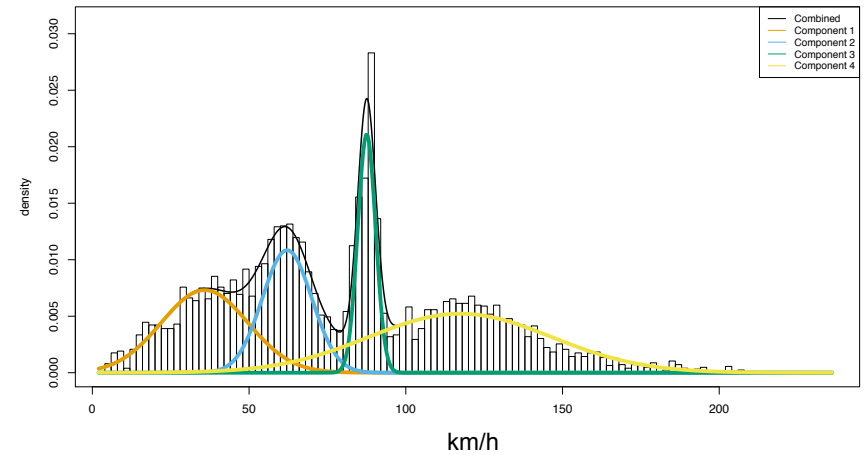
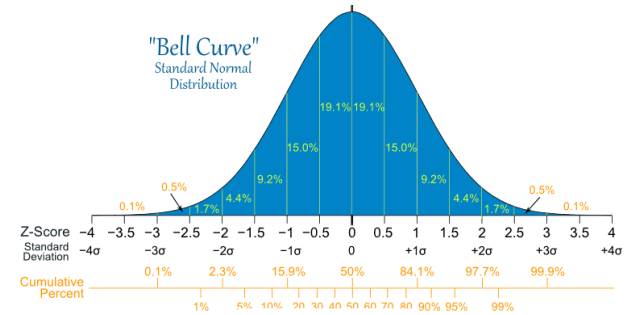
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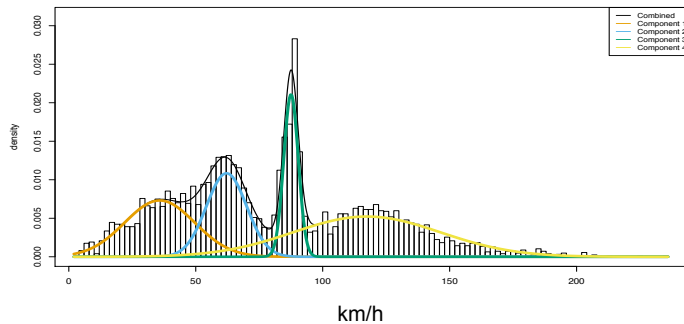
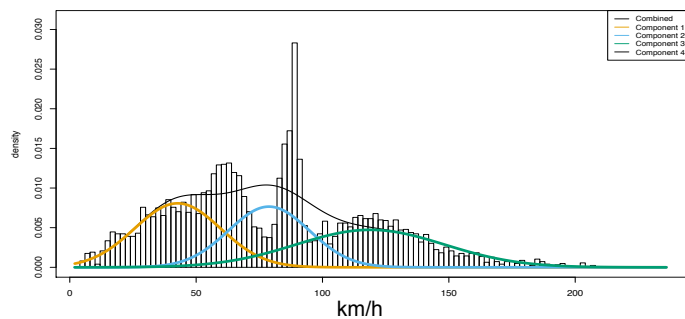
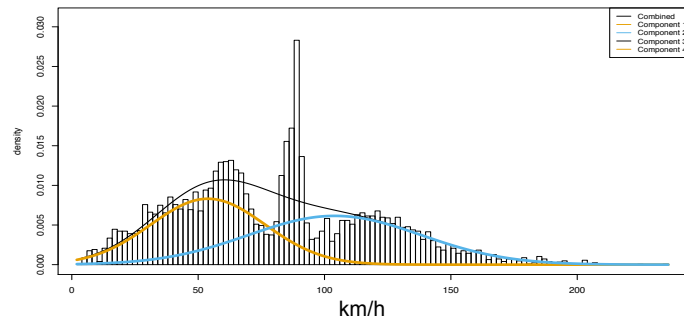
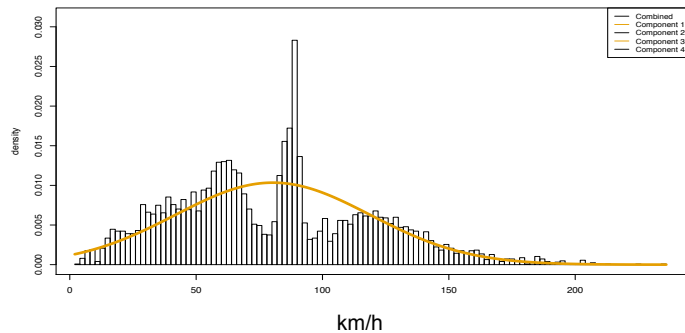
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Find Velocity Groups

- Velocity distributions can be **fit well** with Gaussians
- An ‘overlay’ of multiple Gaussians is called **Gaussian Mixture Model**
- GMM fitting of the velocity distribution is done by **Expectation-Maximization** algorithm
- Shapes and positions of Gaussians **determine velocity groups**

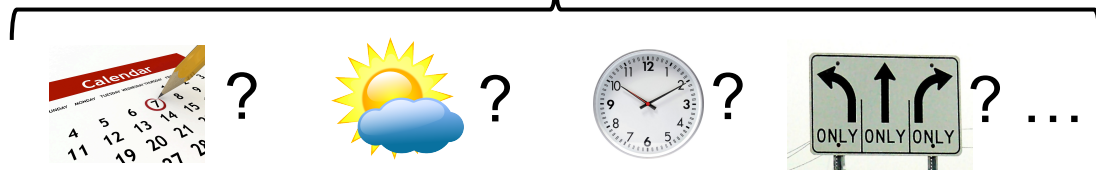
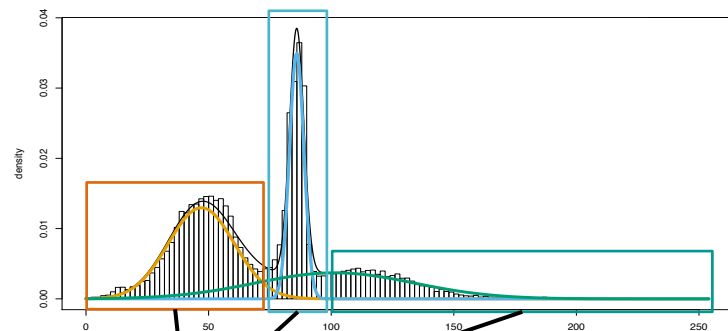


Gaussian Mixture Model



Predict Gaussians

- The second step seeks to explain/predict which Gaussian a data point belongs to
 - Classification task!
- Features for classification:
 - Time of day, day of week
 - Weather
 - Direction
 - Special Events
 - ...



White and Black Boxes

- Analyze correlations between **features** of a data point and its **assignment** to a Gaussian
- From a Machine Learning point of view, this is **classification**



- Generate an *interpretable* model description

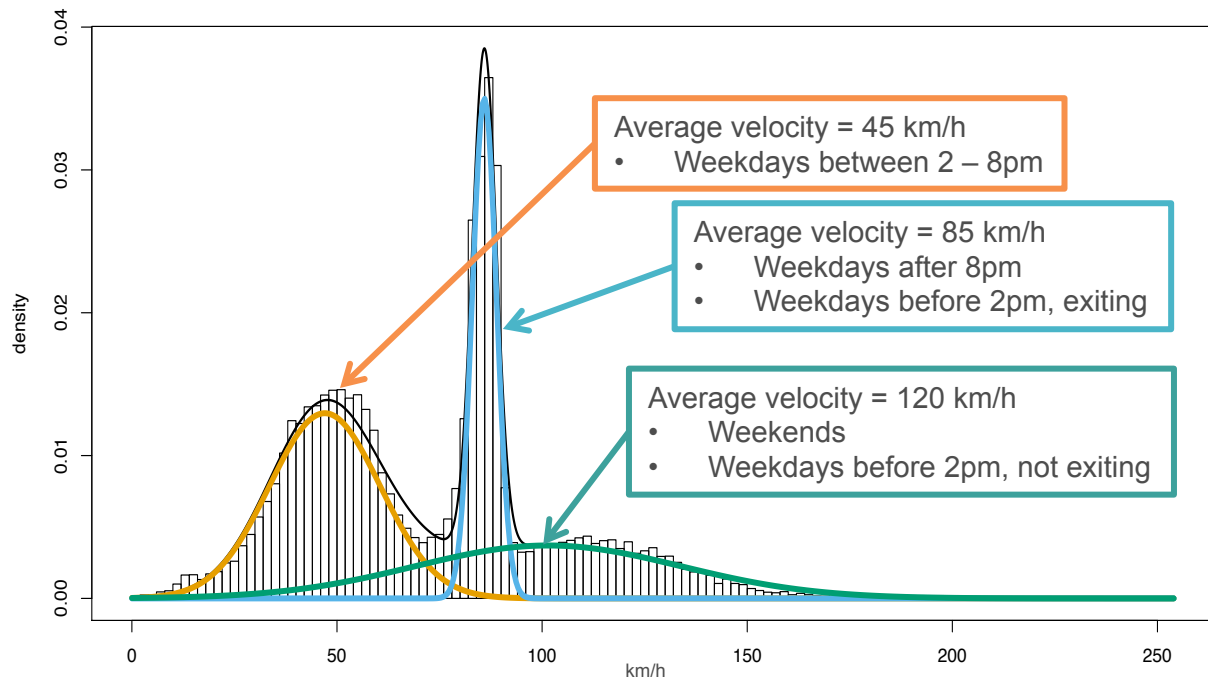
➤ **Explanation** of behavior



- Can capture *more complex correlations*

➤ **Prediction** of Gaussian assignment

Putting it all together...



Two-Step algorithm: GMM + Classification

- Identified multiple velocity profiles for every road segment
- Intuitive and easily interpretable results
- Highly scalable for more features and data

Better Travel Time Prediction

- **Traffic profiles emerged from data**

- Without using metadata, we uncovered road segment traffic patterns



- **Identified Bias Effects**

- Inferring the *impact of turns* and *day of week* on velocity
- Able to predict *rush hour* by day and time by road segment



- **Traffic Light Patterns**

- Infer *public transportation* effects on traffic
- Automatically determine different *switching patterns*



London Road Traffic Disruptions

Can we predict when unexpected incidents will end?

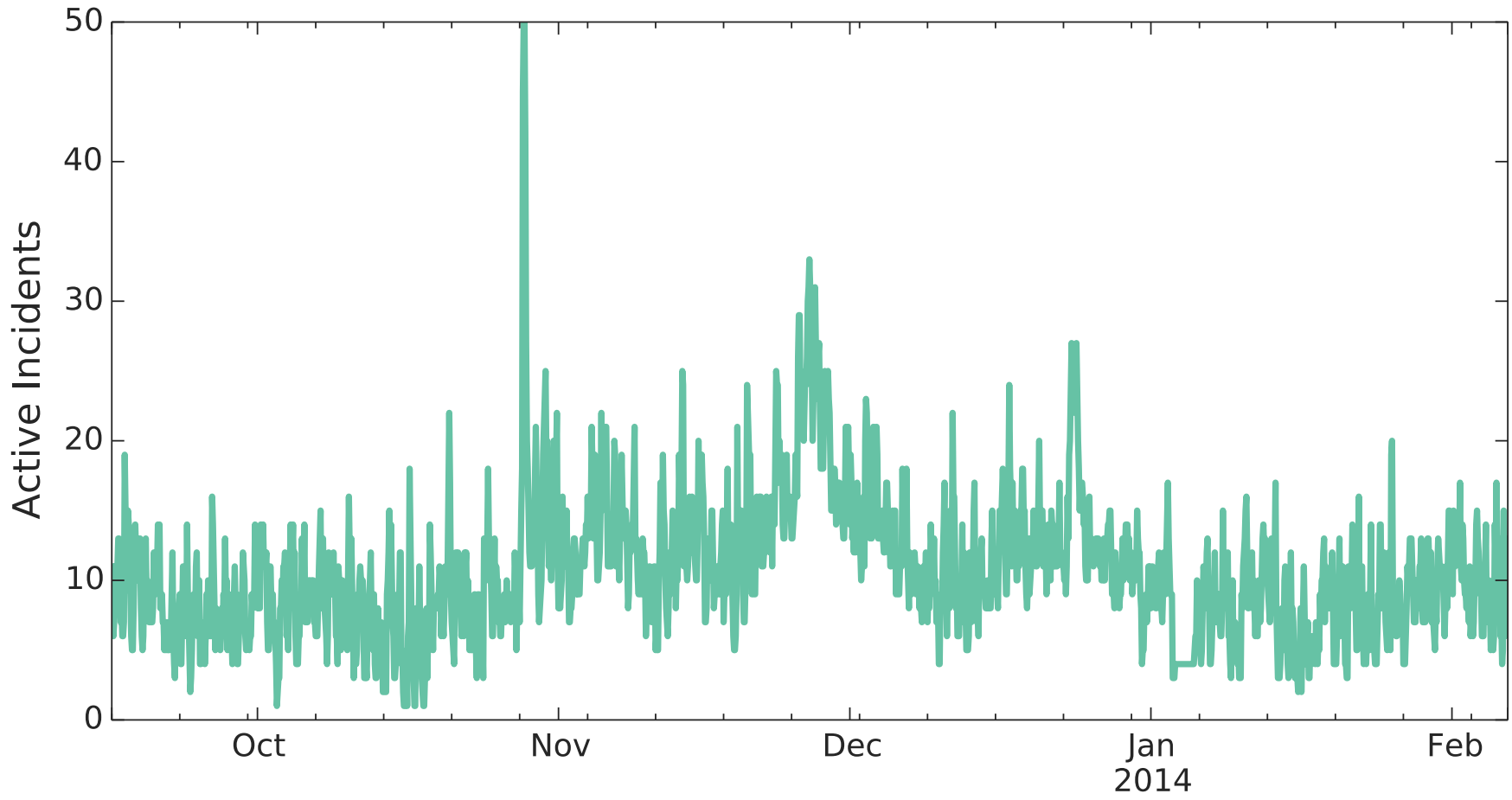
Publicly available data:

- Transport for London traffic feed (refreshed every 5 minutes)
- Weather Underground reports

Photo by James Blunt Photography on Flickr (CC BY-ND 2.0)

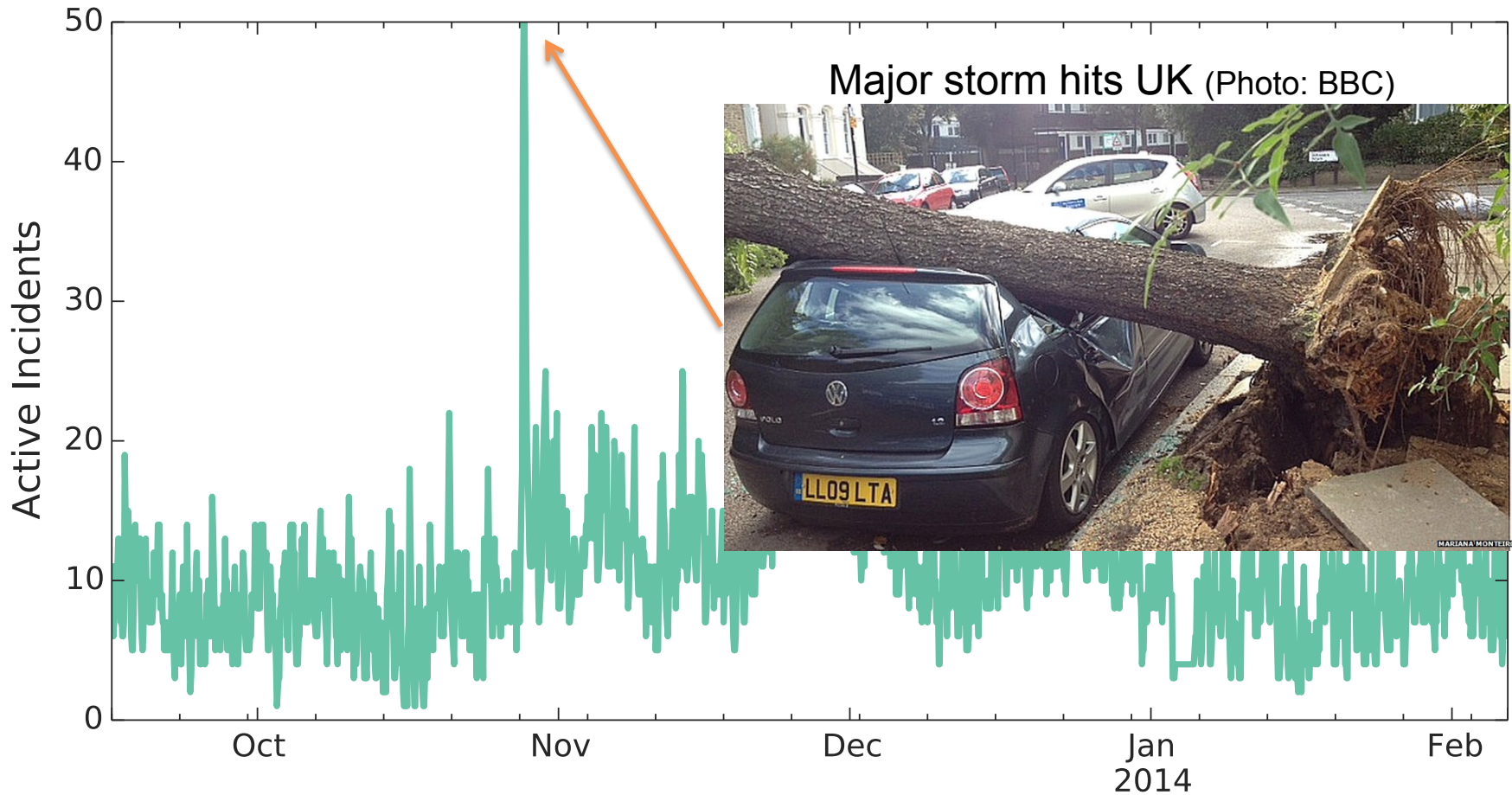
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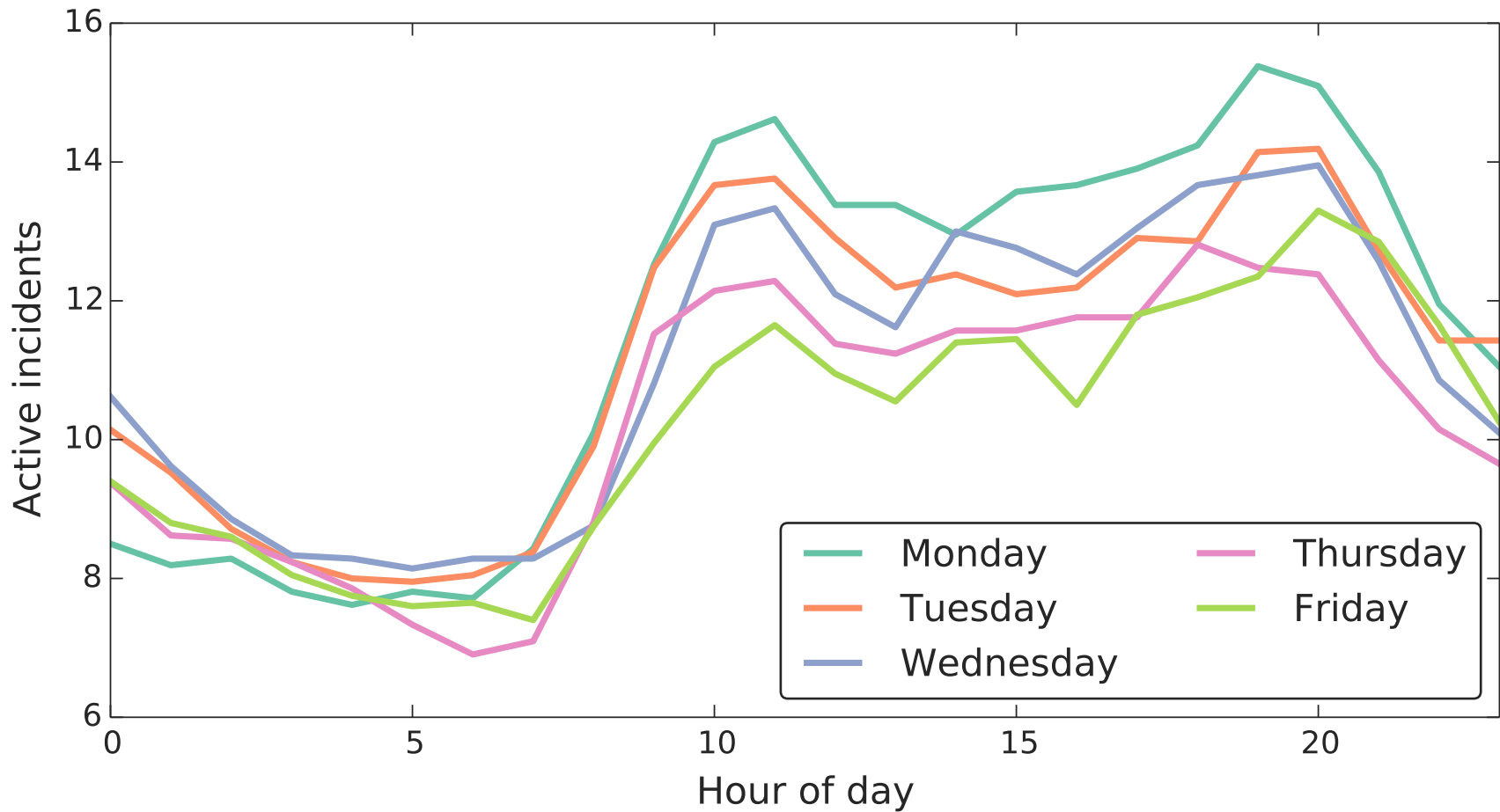
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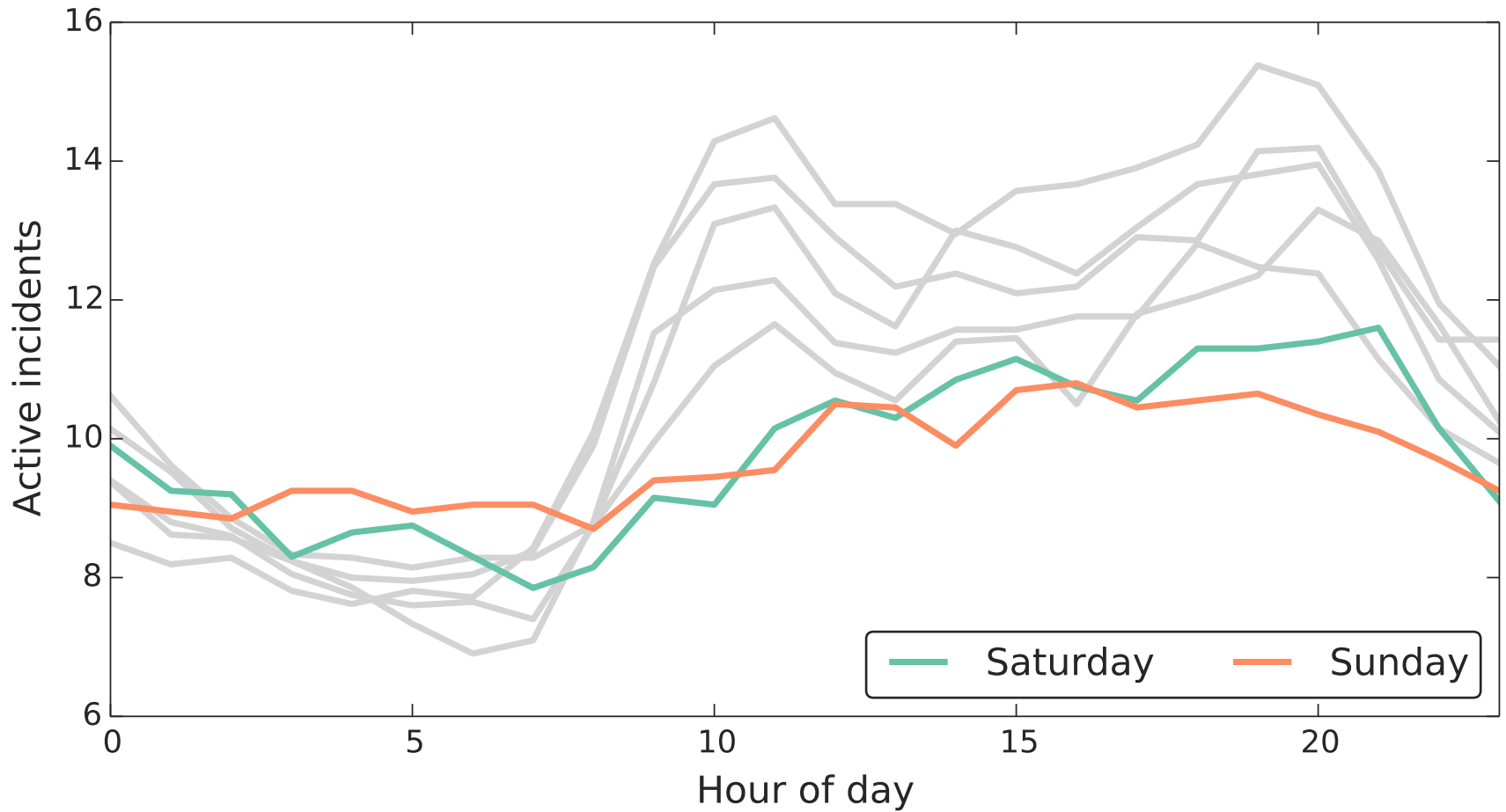
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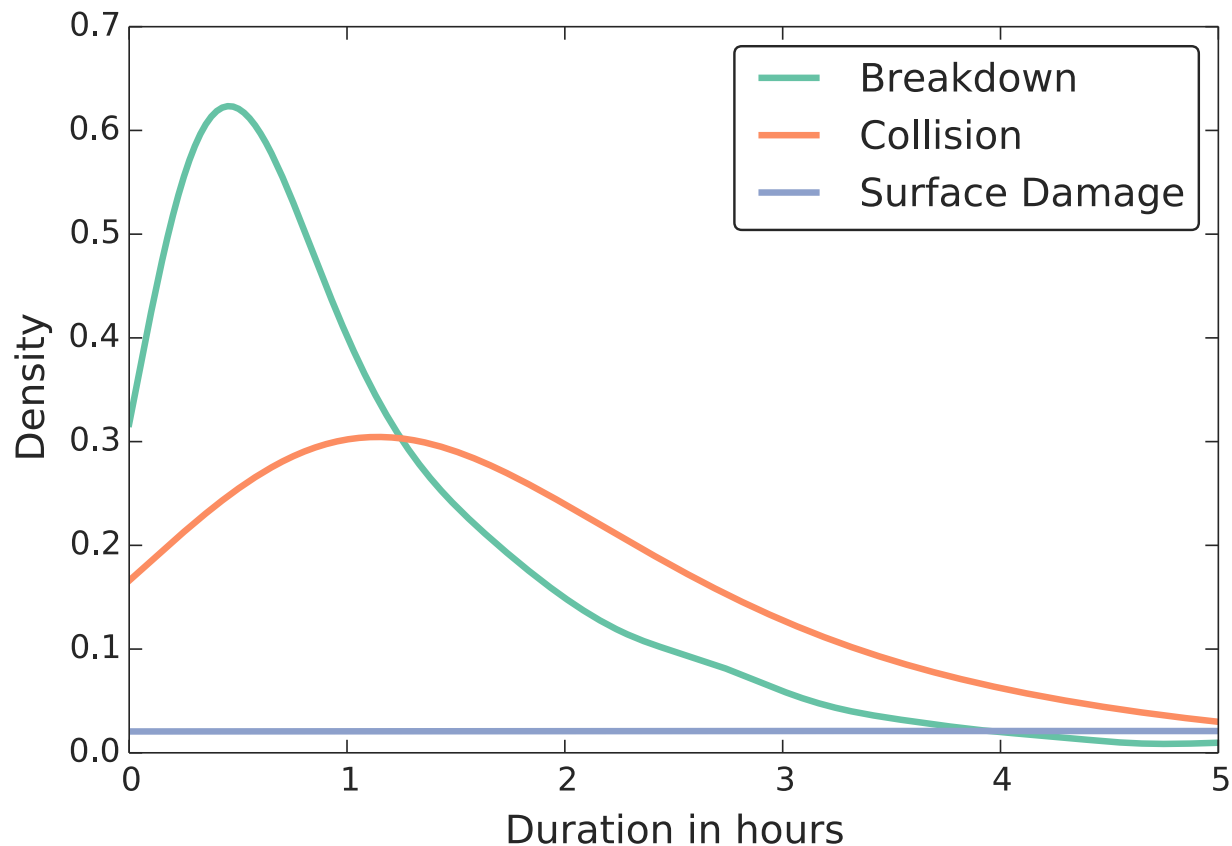
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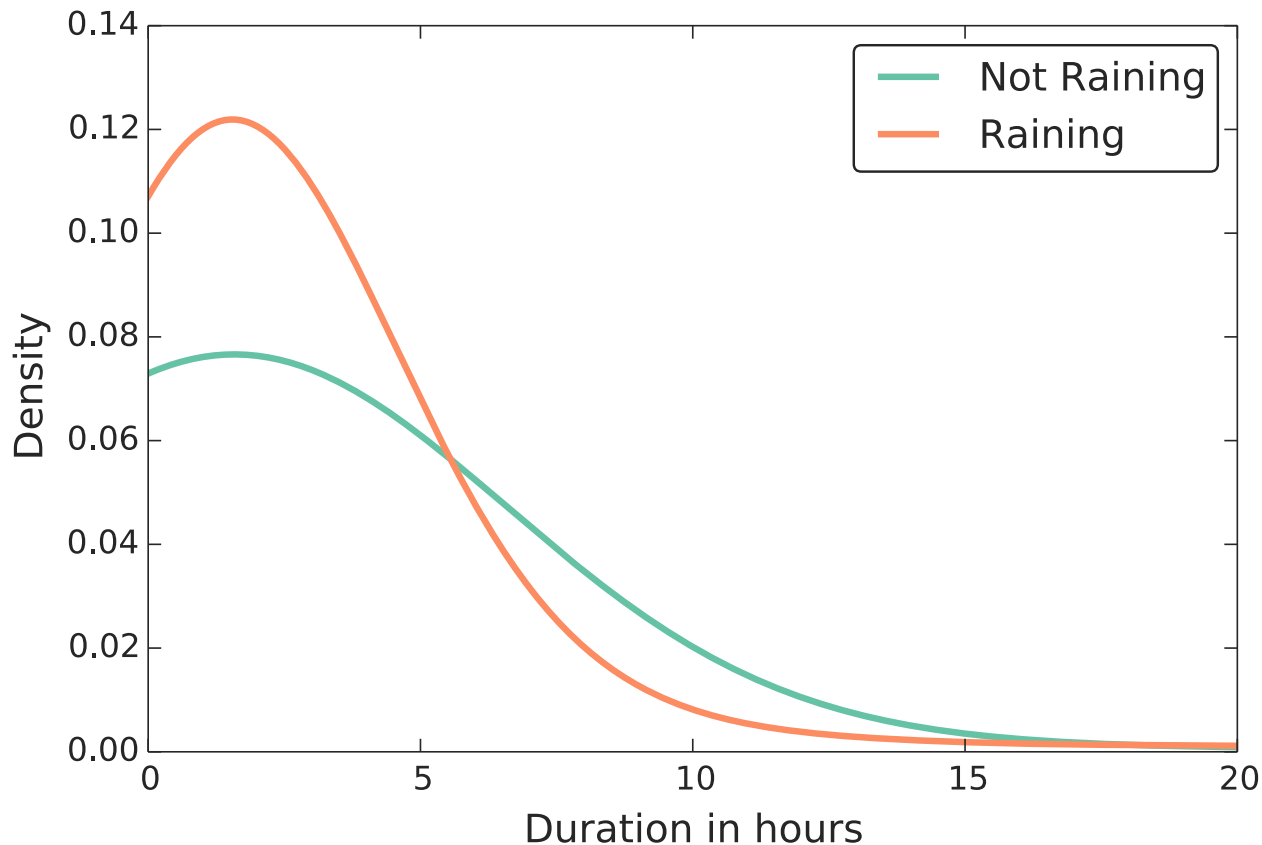
Durations are very different for different types of incident.

Mean duration for Surface Damage incidents is 107 hours!



Rain affects duration in a surprising way.

Incidents which start when it is raining finish **faster** than others.



Models

Linear Regression

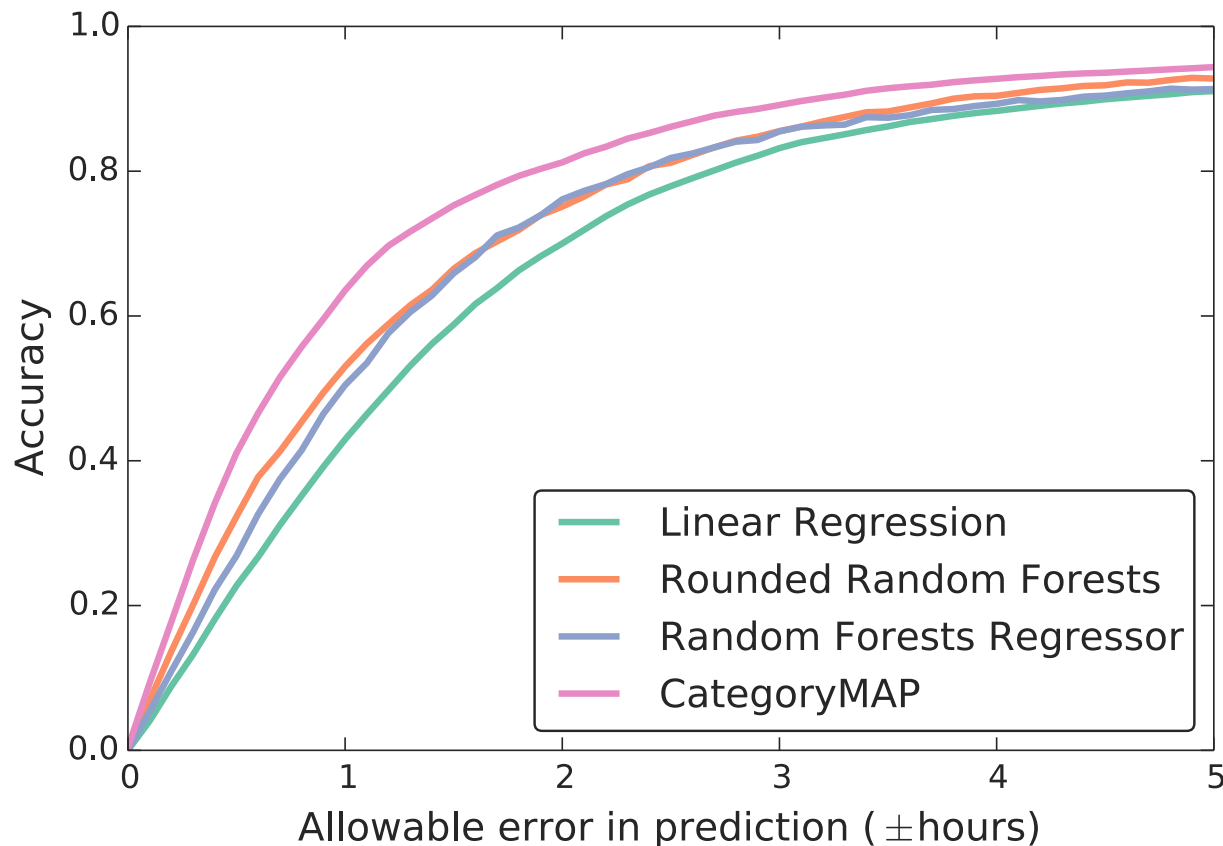
- Disruption reports & weather features

Random Forests

- Rounded categorical
- Regression

Category MAP

- Only use category of incident
- Maximum Likelihood estimate



Live Predictions

<http://ds-demo-transport.cfapps.io>

Using:

Pivotal™
Greenplum® Database



Pivotal CF™

Active Incidents and Predicted Durations

Transport for London Data					Predictions	
Start Time	Location of Incident	# Streets Affected	Type of Incident	Total Duration	Time Remaining	
Thursday, 6 Feb 14 20:40 Greenwich Mean Time	[A10] Turkey Street (EN1) (Enfield)	2	Flooding	4.2 hours	2.7 hours	
Thursday, 6 Feb 14 21:00 Greenwich Mean Time	[A40] Western Avenue (HA4 ,UB5) (Hillingdon)	2	Flooding	4.2 hours	3 hours	
Thursday, 6 Feb 14 20:44 Greenwich Mean Time	[A406] North Circular Road (E12) (Newham)	1	Fire	2.2 hours	Up to 1 hour	
Thursday, 6 Feb 14 21:12 Greenwich Mean Time	[A205] Dulwich Common (SE22) (Southwark)	3	Collision	1.1 hours	Up to 30 minutes	

Using 231209 reports about 9036 incidents since September 2013. Latest Update: Thursday, 6 Feb 14 21:50 Greenwich Mean Time

@ianhuston, @gopivotal

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Summary

- Making use of a vibrant ecosystem of traffic data
- Innovative approaches needed to generate value from abundant and complex sources
- Connecting predictive models to traffic in the physical world is the future of smart cities

Thank You!

Check out more of our Data Science use-cases at
www.goPivotal.com

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