Geoplace Conference
Thursday 9 May 2019

LONDON FIRE BRIGADE

NFCC
National Fire
Chiefs Council

Apollo Gerolymbos

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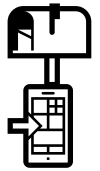
Data Lead – National Fire Chiefs Council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@Apollo_LFB

Agenda

- History
- Who we are
- Who we work with
- Examples of work
- Where next?

London Overview

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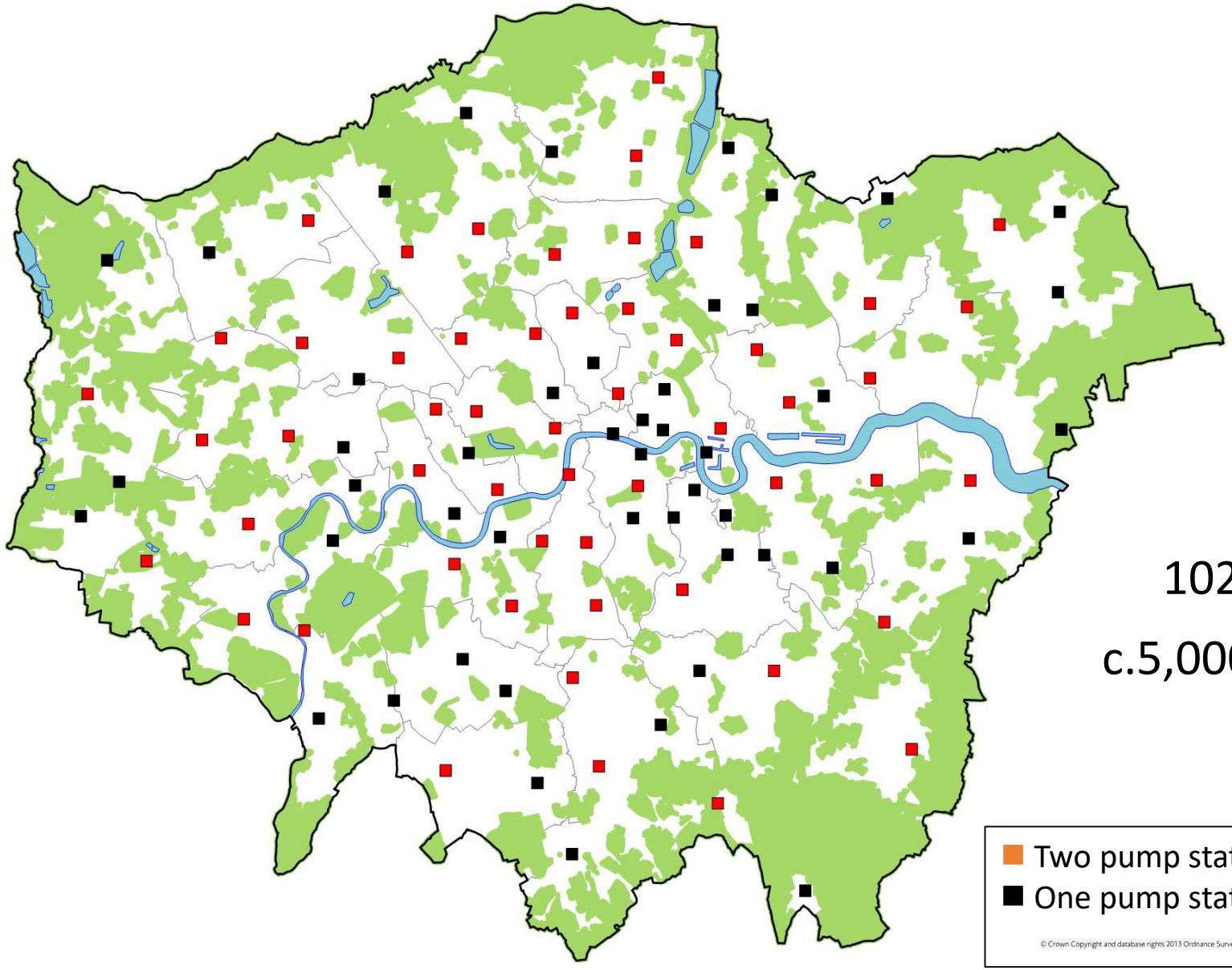


1,572 km², 8.8m people

c.3.5m homes

c.900k businesses

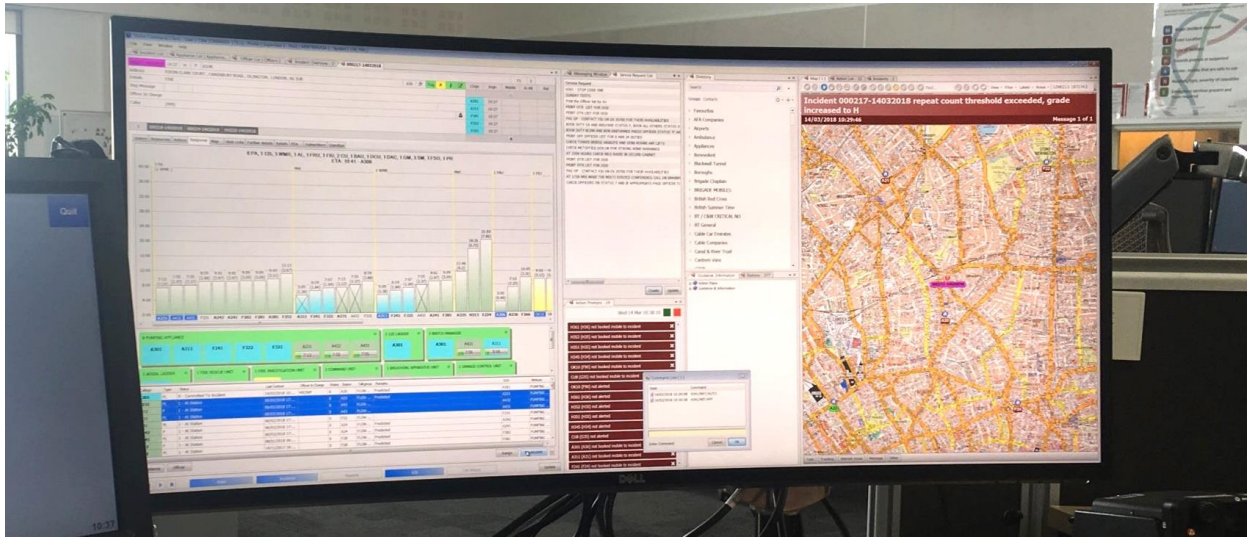
32+1 boroughs, 654 wards

102 fire stations, 142 fire engines

c.5,000 operational / 800 office staff

105,000 incidents attended

LFB have come a long way…



…but what about data science and analytics?

Cholera outbreak map, John Snow, Charles Cheffins

?

Who are we?

- Interdisciplinary team
- 12 people

Who do we work with?

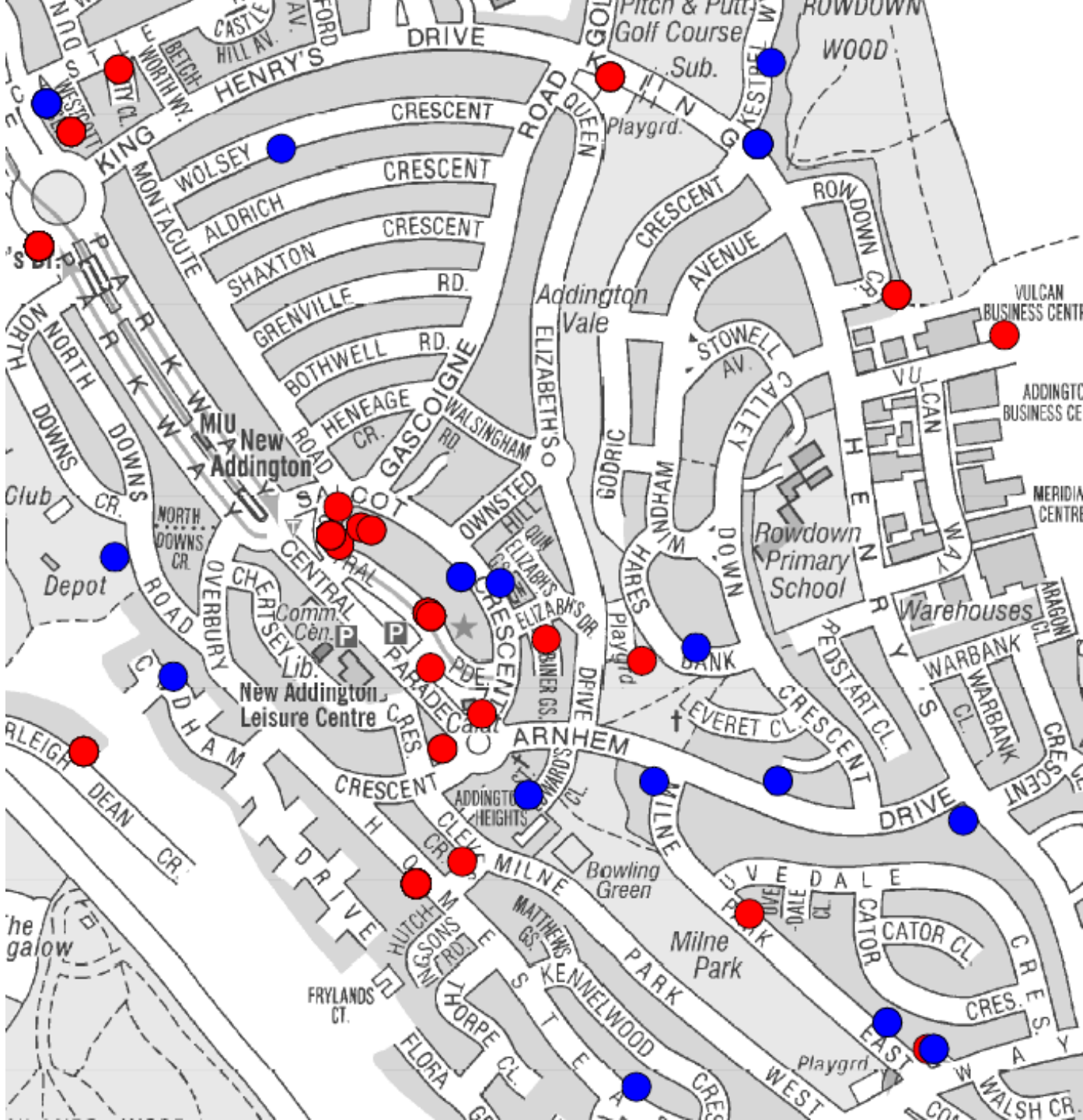
- Fire Investigation
- Community Safety
- Operational Tactics
- Special Operations Group (CT, MTFA)
- Local Authorities / Area teams
- Borough commanders, Station Managers
- Communications / Press Team
- Information Access (FOI/SAR)
- 999 / Mobilising

Microsoft SQL Server

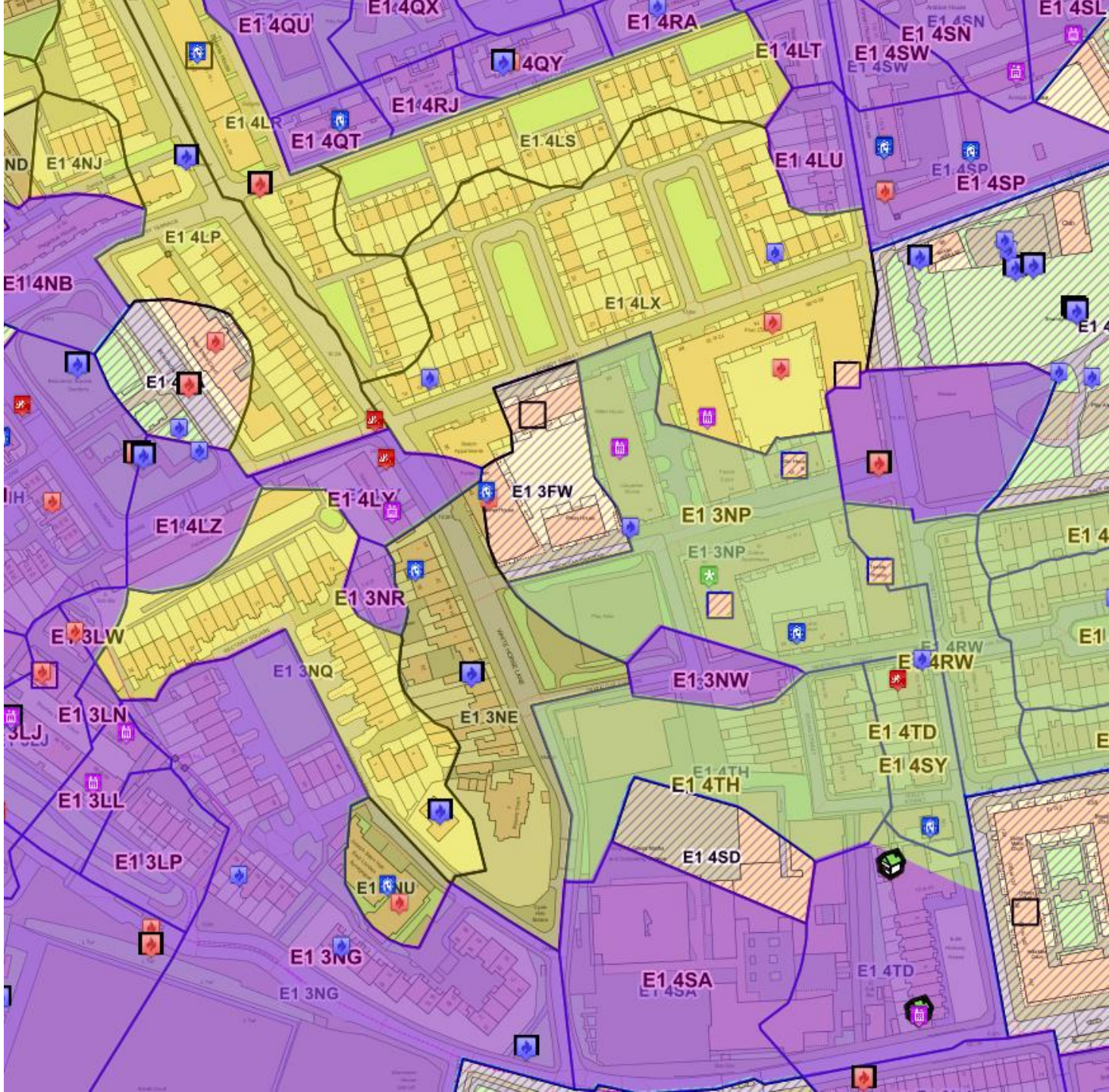
Cadcorp®
WORLD LEADING GIS SOFTWARE

Experian
A world of insight

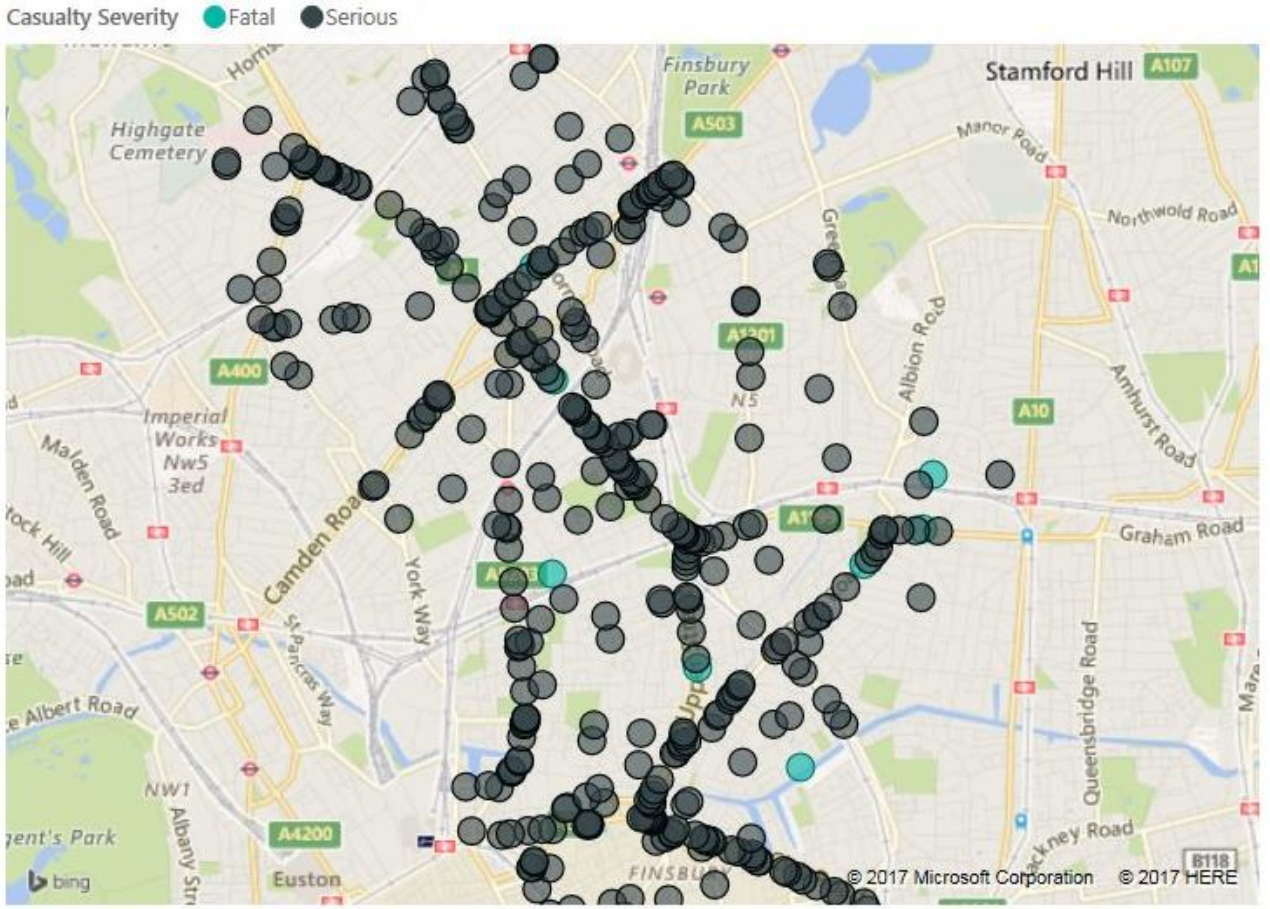
Power BI

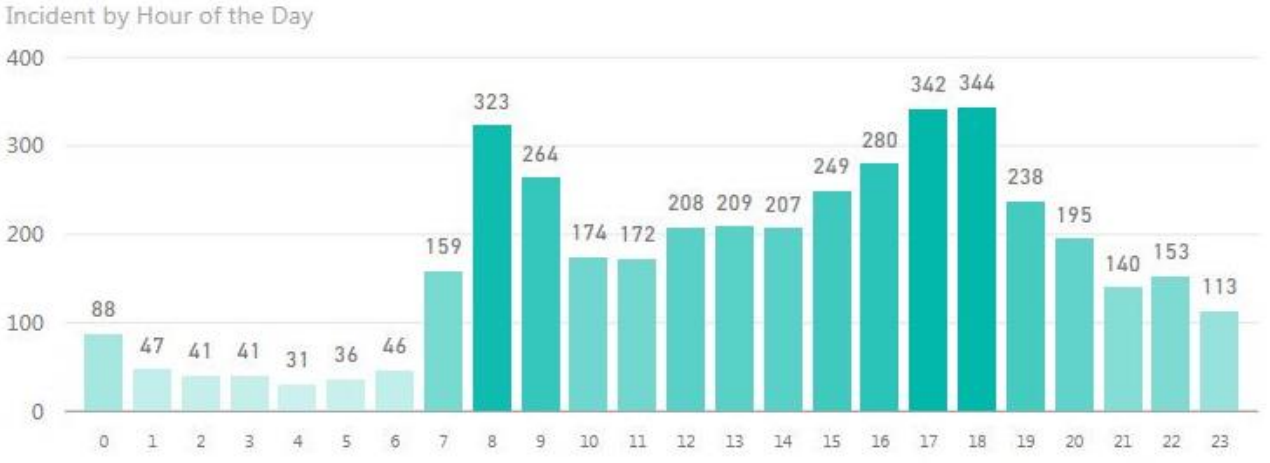


- We have in house systems that allow our firefighters to interrogate datasets that sit behind the scenes.
- In this instance they are looking at an area in East London, with an overlay of Experian Mosaic demographic data that we use to help target our home fire safety visits at the most vulnerable.
- Firefighters can also overlay prior incidents to find the most “risky” areas.
  - More on that later…

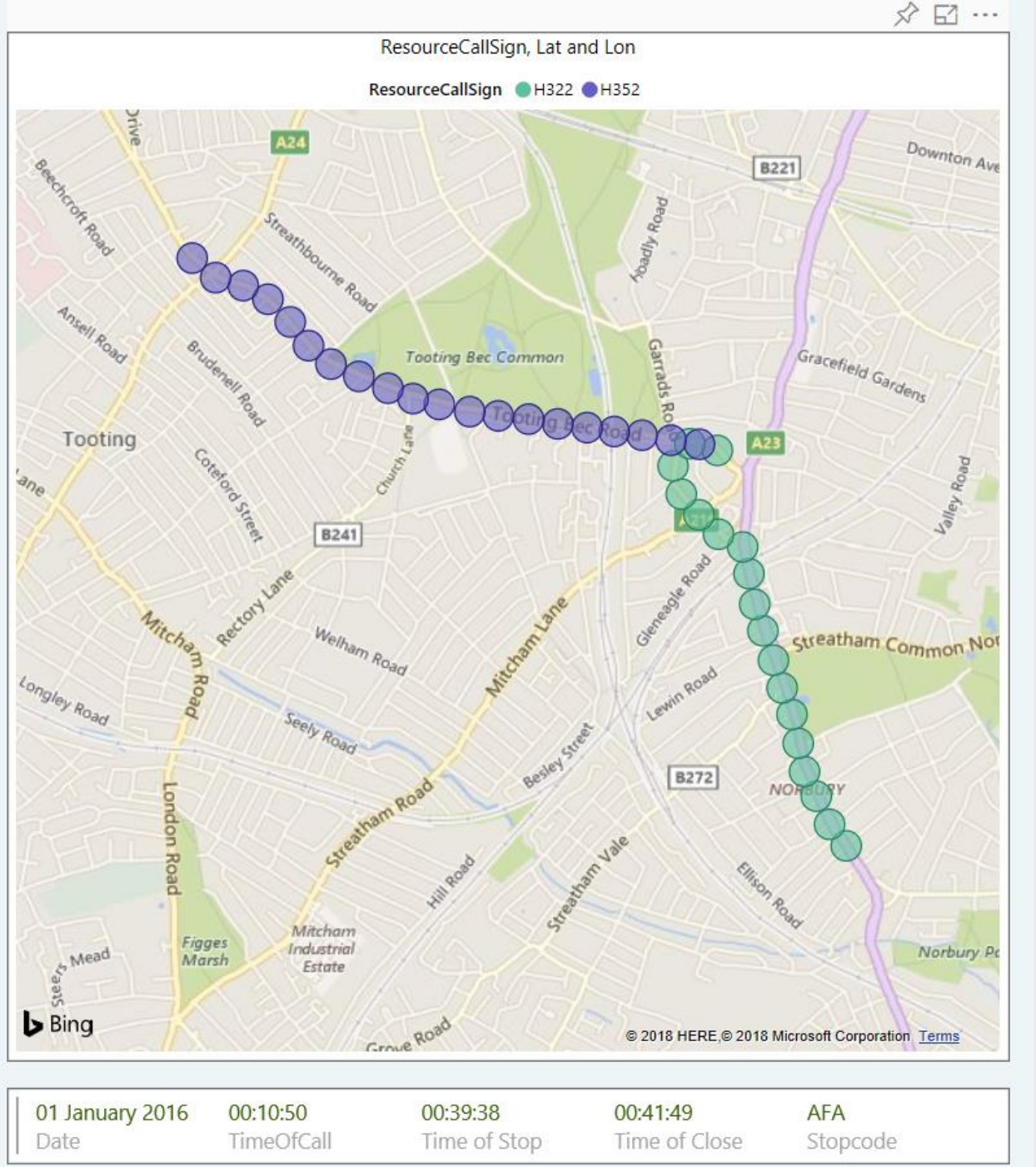


- We also publish and pull in open data from other organisations where available
- https://data.london.gov.uk/
- In this instance we created an interactive road safety dashboard combining LFB road traffic collision data with TfL road traffic collision data to better understand where these incidents occur in London
- This map is for Islington with a breakdown by hour of the day
- BI Project (Power BI)

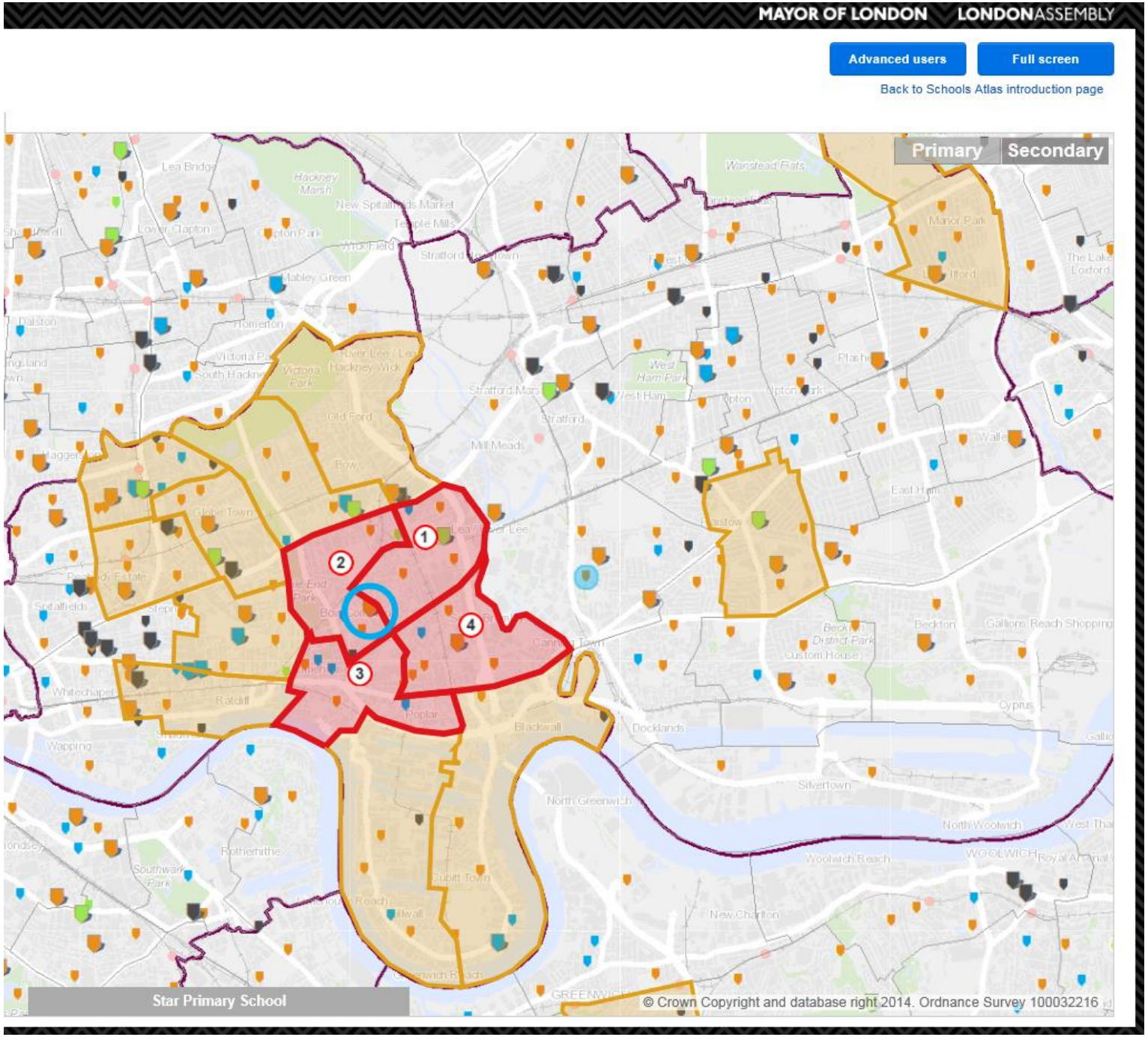


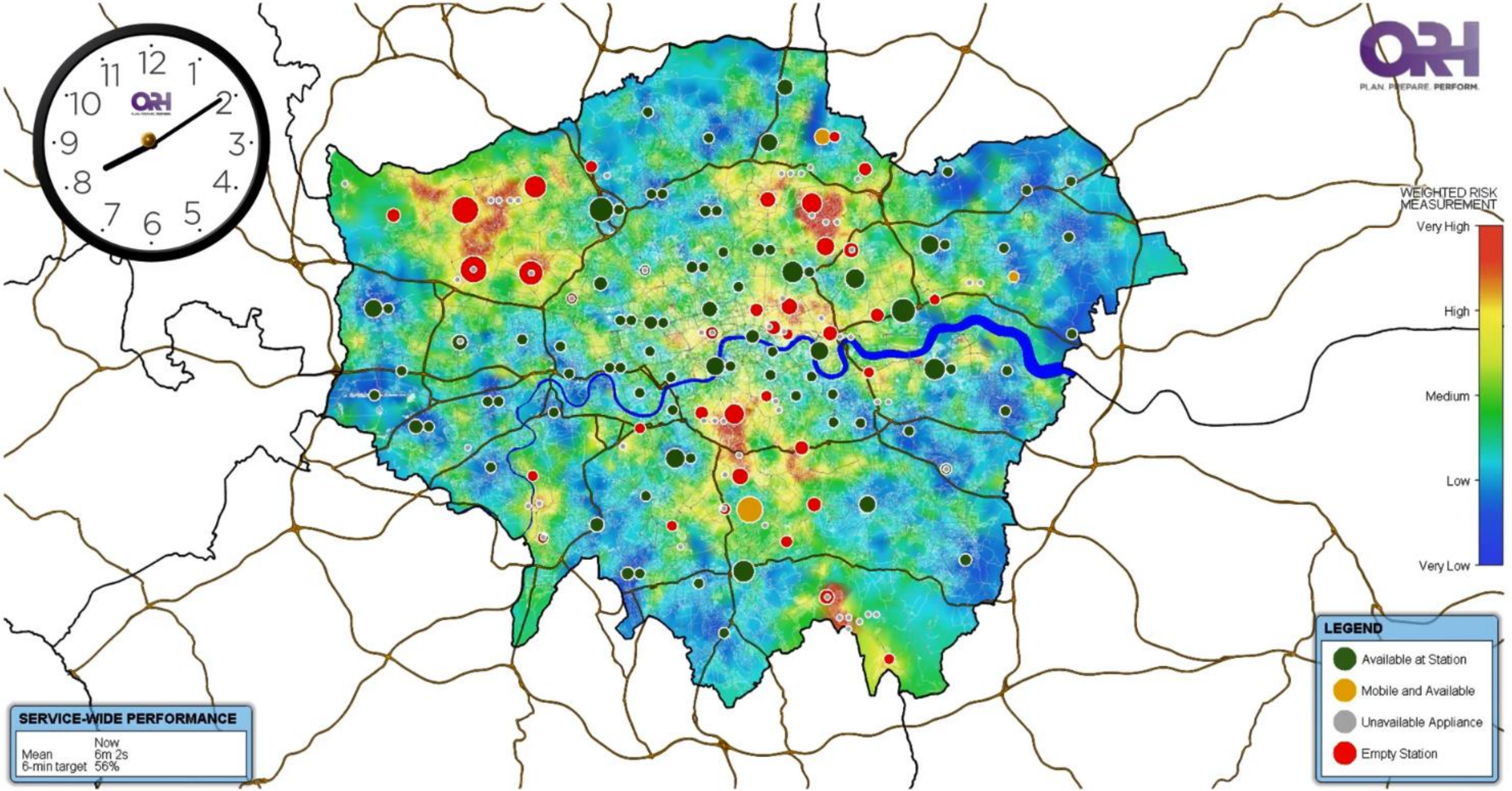


- We have access to the data from our Vision mobilising system and the location of fire engines via the GPS pings
- In this case we have to snap points to roads in order to produce interactive dashboards showing appliance routes to incidents.
- Saves substantial time over producing PDF maps on an ad hoc basis

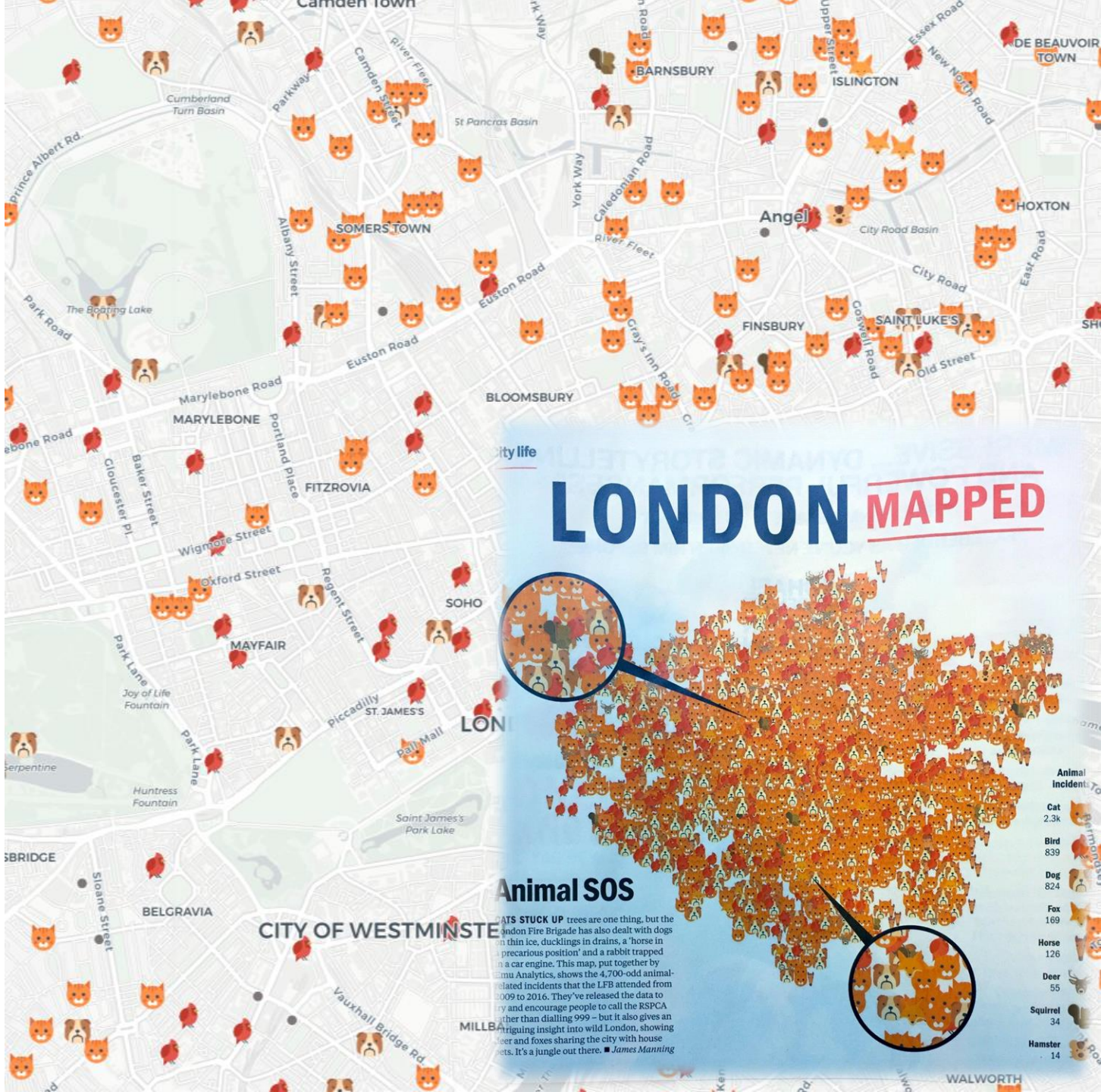


- Apart from the 80,000 HFSVs per year, we also visit about 1000 schools.
- These are ranked by a risk score and prioritised as such
- We use open data about schools and where pupils that attend each school live
- Results in better targeting of school visits based on the demographic characteristics of a child's home to build up profiles of risk at each school



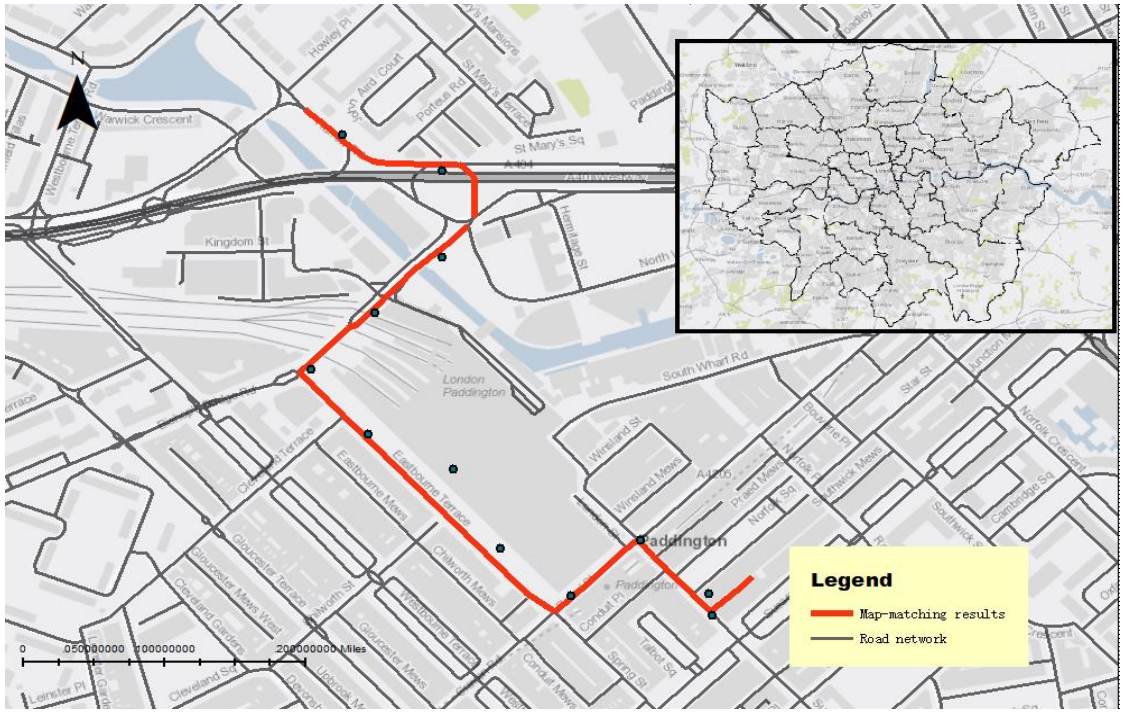

PLAN. PREPARE. PERFORM.
WEIGHTED RISK MEASUREMENT
Very High
High
Medium
Low
Very Low
LEGEND
Available at Station
Mobile and Available
Unavailable Appliance
Empty Station
SERVICE-WIDE PERFORMANCE
Now
Mean 6m 2s
6-min target 56%

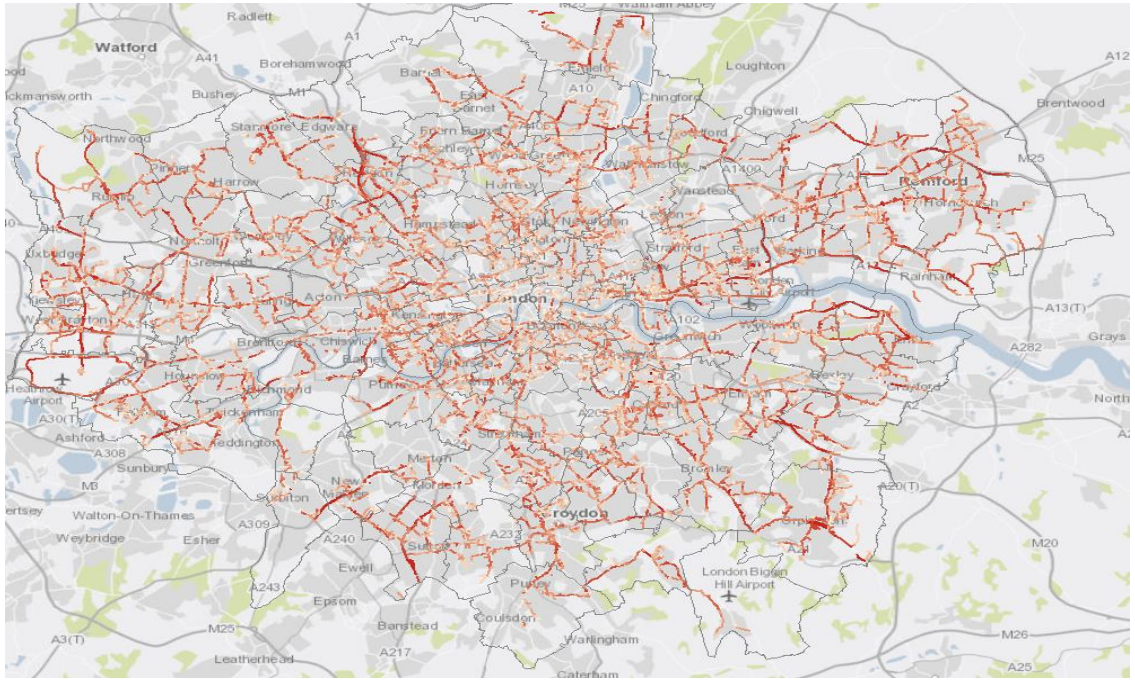
- Occasionally third parties pick up our open data and run with it.
- In this instance, Emu Analytics created an interactive map of all our animal rescues since 2009 and this was featured in TimeOut
- The result of this work is a good example of the public engaging with FRS data
- Helps our recruitment drives and interest from third parties like academia…



Academic collabs

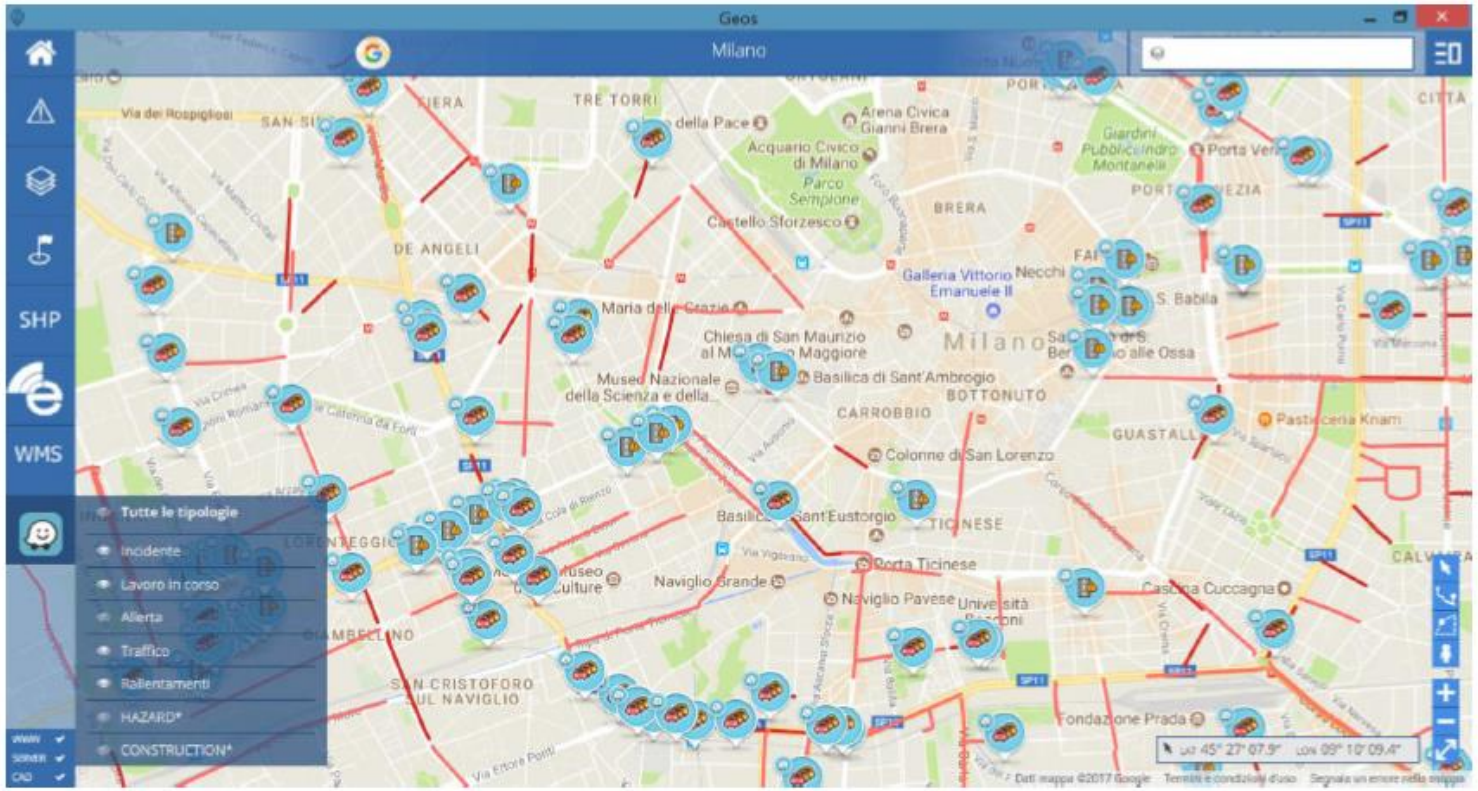
- MSc project with UCL SpaceTimeLab for big data analytics
- Station grounds vs geographic mobilising
- 23 seconds faster compared with 2015
- Compare predicted vs actual attendance times
- Use spatial and temporal analytics algorithms to evaluate road speed impact on mobilising
- Potential for further improvements





EENA/WAZE PILOT TEST PROGRAMME

Evaluating the use of Waze in emergency response & its impact on response operations



Using EPC data to target prevention

(Tudor Thomas, Faculty data science fellowship)

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Major aims of the project:

1. To build an all-addresses corporate database (AACD) which joins all the information known by LFB for every addressable point in London
2. To use the AACD to build a model which is able to accurately predict historical fires
3. To use the AACD and model to forecast fire risk
4. To understand which metrics correlate best with fire risk, and therefore which datasets to interrogate and develop further

1) Building the AACD

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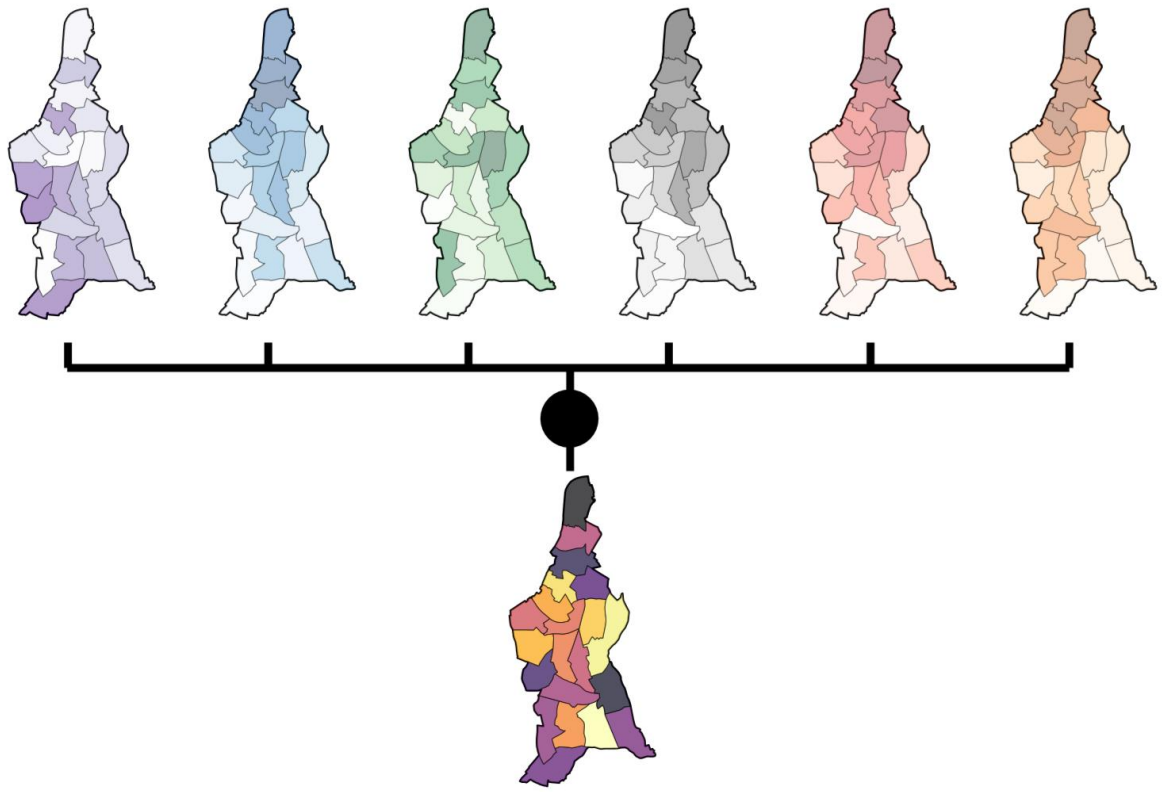
Dataset	Description	Index/ identifier	Cleaning required	Source
ABP	Address and UPRN of all addressable points near London	UPRN, Parent UPRN	Determining which UPRNs were inside London.	AddressBase Premium
Heights	Heights of all buildings near London	UPRN, TOID	As above	OS MasterMap
EPC	Energy performance certificates for households in the UK	UPRN	As above, and determining which records were current at the time of fire, and which records are current.	GeoPlace
Mosaic	Demographic data on a household level	UPRN	None	Experian
Location Feat	Borough, ward, fire station, DAC area of building	UPRN, TOID	Recursively finds building polygons (from heights) in any shapefile. As wards/fire stations change, this can be updated	Generated by Tudor
Fire details	Details of all historical fires attended by LFB since 2009	UPRN	Used only accidental (not deliberate) fires inside properties (primary fires).	LFB

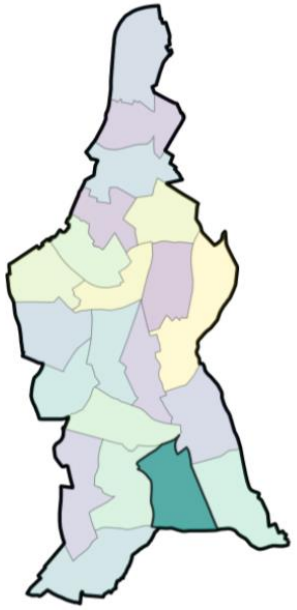
2) Predicting historical fires

- tree-based classifiers gave similar accuracy to k-nearest neighbours, support vector machines and neural networks
- advantages
  - fast to train
  - interpretability was desirable
- final model was a Gradient Tree Boosting model (of 200 trees), and correctly predicted true negatives 66% of the time



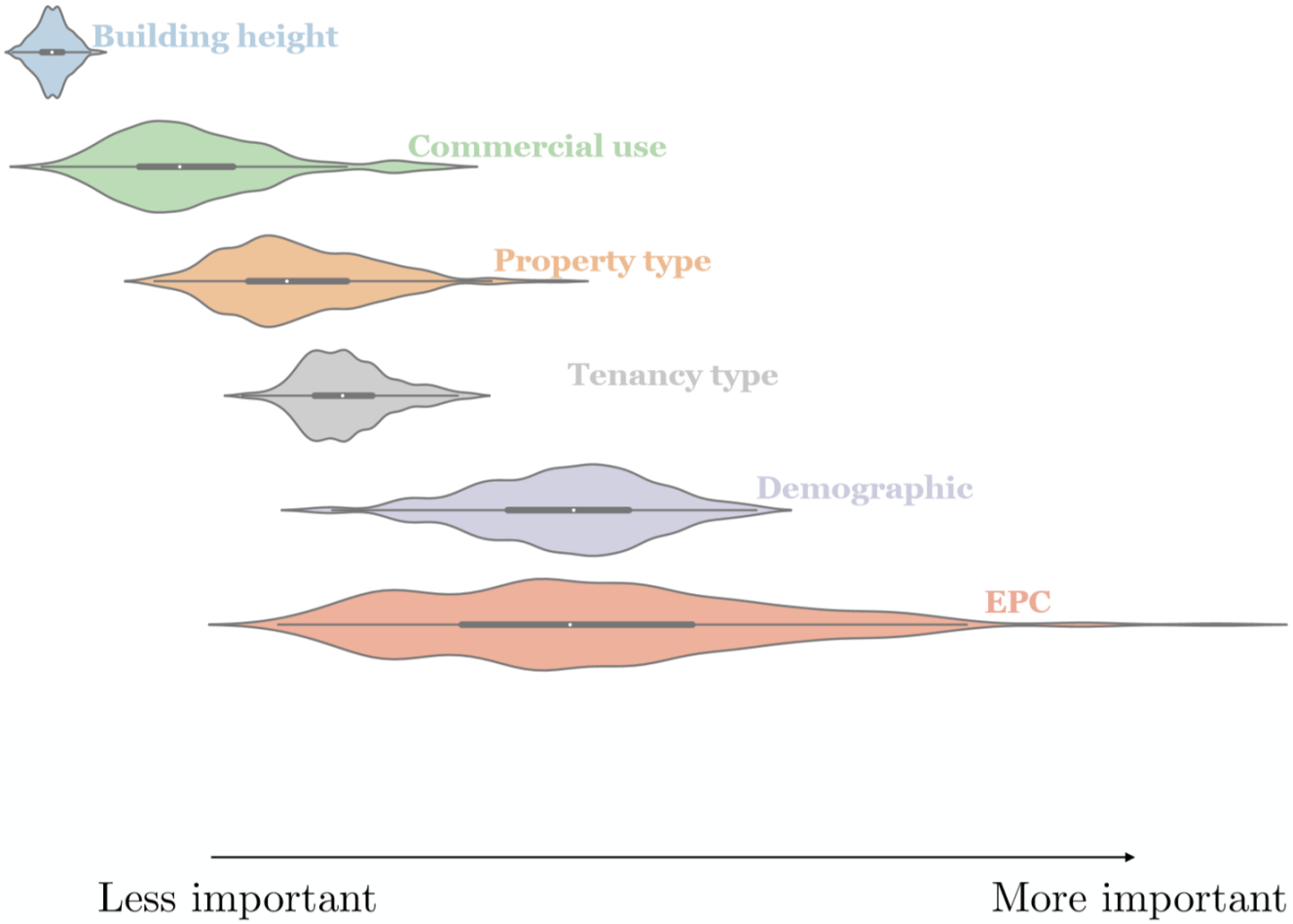
3) Forecasting fire risk

- forecasting task involves predicting based on only the most recent records of the AACD
- Since the EPC data is currently the only data source in the model which contains both up-to-date information and historical information, forecasting was simply a matter of filtering these rows, and applying predict to the classifier
- Ward-averaged fire risk (left), and at the household-level in the Knight's Hill ward (right).



4) Feature importance

- tree-based models are transparent in their interpretation
- meaningful predictions did not use building height data
- the opposite is true for demographic and EPC data
- for some subsets of the data, columns in the EPC data are by far the most important towards accurate prediction



What next?

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- Use proof of concepts to successfully apply for a growth bid
- Use funds to build an in house data science capability
- Use more data, better
- Take advantages of advanced techniques on new datatypes
- Develop relationships and learn
- Publish, share and collaborate with other fire services, nationally and internationally

…so what about data science and analytics?

Cholera outbreak map, John Snow, Charles Cheffins

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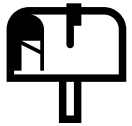
Thank you

 apollo.gerolymbos@london-fire.gov.uk

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