Smart London

Dr Stephen Lorimer
Greater London Authority
E: stephen.lorimer@london.gov.uk
T: @slorimer44 @mayoroflondon #smartlondon
W: medium.com/@smartlondon
CITY GOVERNMENT AND SMART LONDON

Creative
Creative industries
Cultural institutions

Scientific
World-class universities & research
MedTech

Data economy
40+ tech clusters 47k tech businesses
Growth sectors (CleanTech, GovTech)

Mayor of London
Strategies for Transport for London, policing, fire, environment, economic development, skills and planning

Health and Education
Hospitals, GPs, universities, and research institutions

33 London boroughs
Social services and other local services like waste, public health, libraries

Utilities
Water, Gas, Electricity
Telecoms and broadband providers, Train Operating Companies

Planning
New London Plan
Future guidance

Delivery
Transport
Policing
Skills
Health

Civic
Non-stat plans ‘Convening power’

Budgetary
Grant-making
THAT MAP....
FCC study of 21 cities globally

- Local governments lack the capacity to understand, develop and implement smart city strategies - requires senior leadership.
- Need to be embedded in statutory frameworks and plans.
- For a smart city that is adopted by people and therefore impactful, a collaborative approach is required.
- Most smart city funding is still derived from innovation pots and not linked to core city funding.
- Smart city leads should consider how to give clarity to potential private sector partners.
Big systems

Citizen-centric services
Chief Digital Officer & Smart London

**Leadership**
- Shared digital vision, outcomes & language across GLA
- Capacity-building at GLA and councils

**Collaboration**
- Scoping foundations with boroughs (LOTI)
- Mobilising public sector assets

**Innovation**
- Innovation story
- London Tech Week 2018 - Smart City & Women-in-Tech themes

---

**New Smart London Plan**
- Delivery-focus - 20 actions for London
- Partnership with Bloomberg Associates
- Driven by Smart London Board
- Starts with major Listening Exercise
- Launch Q2 2018

---

Theo Blackwell
Chief Digital Officer for London
Greater London Authority
A ‘Smarter London’ uses data and technology together for the good growth of our city. It mobilises the power of data as the fuel for innovation to design and develop safe, open and inclusive solutions for city growth challenges London faces over the next decade and beyond.

To stay ahead of the technology curve, rather than follow it, a Smarter London needs new city-wide collaboration between public institutions, utilities, our world-class creative, scientific research and tech communities by and for Londoners.
Smart ‘enablers’

- ‘New Deal’ for city data
- Digital talent & capability
- World-class connectivity
- City-wide collaboration & innovation
- Openness & inclusivity

Data capital
Smart London

Dr Stephen Lorimer
Greater London Authority
E: stephen.lorimer@london.gov.uk
T: @slorimer44 @mayoroflondon #smartlondon
W: medium.com/@smartlondon
“The search for HMOs: Can machine learning help?”

Barking & Dagenham’s model to assist in the identification of Houses in Multiple Occupation

Pye Nyunt & Phil Canham
Corporate Insight Hub
28th March 2018
Artificial Intelligence

An intelligent agent that perceives its environment and makes decisions to maximise chances of achieving its goal.

Sub-fields of AI:

Machine Learning  Robotics  Natural Language Processing

Machine Learning

Giving computers the ability to learn without being explicitly programmed

Supervised Learning
  Classification, Regression

Unsupervised Learning
  Clustering, dimensionality, reduction, recommendation

Reinforcement Learning
  Reward Maximisation
Change in Private Rented Sector since 1981: LBBD

source:
Census 1981 to 2011
LBBD_Administrative data 2012-2017
Aims and definitions

• To provide a robust model which will enable the identification of potential HMOs

• Significantly improve the chance of discovering a new HMO compared to random property selection.

• The aim is not to replace but rather to strengthen the current procedures used by enforcement to identify HMOs

• The definition of HMOs is defined here to coincide with that used by our enforcement service to serve both Mandatory and Additional licences.

• The model will not distinguish between Mandatory and Additional HMOs

• A HMO is a property rented out by at least 3 people who are not from 1 'household' (e.g. a family) but share facilities like the bathroom and kitchen
Steps

- Define, as far as possible, likely tenure for each household in the borough. The definition of tenure is split here into:
  - Social
  - Owner Occupied
  - Private Rented

- Identify all known and licenced HMOs

- Identify and test a range of potential indicators that are more likely to occur for HMOs compared to non HMOs

- Design and evaluate machine learning model which combines the strongest predictors, in the most effective way, enabling an HMO probability/likelihood to be assigned to every household.

- The programming language R was used to undertake all stages in a reproducible way.

- This also allows changes to be made at any stage, as more information is acquired.
Context

• At the time of the initial model building there were 428 licenced HMOs in the borough, comprising 64 Mandatory and 364 Additionally licenced HMOs

• About 75,000 households in total on our Council Tax Register

• So currently licenced HMOs make up only 0.6% of all households!!!!

• Needle in a haystack!
Based on our current knowledge

If we visited properties totally at random we would have visit about 200 properties to find just 1 HMO
Preparation

• The identification, collection, cleaning, and preparation stages by far take the most time
• It is essential that these stages are rigorously undertaken
• Equally essential that persons collating these data have good domain knowledge for each dataset.
• Need to understand the strengths and weakness and sources of bias/error in each dataset
• The fundamental building block is the Unique Property Reference Number (UPRN)
• If the UPRN is not available, the data will need to be address matched, adding a further stage.
• We have developed a bespoke algorithm to undertake this: “Insight Hub Address Matching Algorithm”
Preparation

• Once data is cleaned it is combined into one set with unique records for each UPRN (75000) – so the UPRN is used as the primary and unique key.

• If a dataset has any duplicate UPRNs the data must be grouped and counted or summed to achieve a set of unique records.

• For the combined dataset: the first column records the UPRN, the next contains a binary flag identifying a household as either a known HMO or not, the third a known tenure flag.

• All other columns include information or predictor variables recorded, at this stage as either numeric, or factor variables. At this stage we have not chosen which variables to use in the final model.

• The next stage is to create “dummy” variables for all factor levels.

• For example, for tenure, the tenure variable would be split into three new variables:
  1. Social Rented: Yes/No (1,0)
  2. Private Rented: Yes/No (1,0)
  3. Owner Occupied: Yes/No (1,0)

• This permits greater flexibility in the models that can be created.
Preparation

• We now have a dataset with about 75,000 unique records and 30 plus columns
• Key Variables included

- ASB incidents (taken from Enforcement Database): Property Yes/No over 3 years
- Sidewaste (6 week recording with Refuse service) Extra Rubbish left out with bin: (Yes/No)
- Occupancy: Residents Matrix 2015- cross matching Councils Admin datasets: numeric
- Electors 2015: numeric
- Electors 2017: numeric
- Change in Electors 2015 – 17: numeric
- Habitable Rooms (Energy performance certificates or imputed from Ctax band): numeric
- Change in Surname of Council Tax primary occupant 1 year (Yes/No)
- HB recipient? 2017: Yes/No
- Ctax reduction? Yes/No
- Flat (Yes/No)

• Some variables may covary – not a problem in tree based models
Preparation

• A key point in the analysis was to select only currently licenced and compliant private rented accommodation for the training of the model. This brought the overall total of households down to about 10,000. Not doing this, we believe, may have caused the LODA/NESTA model to underperform.

• Training and Test sets were created from this Private Rented subset: 70% of data in a training set, 30% in test set (data were randomly selected with stratification to ensure an equal balance of the target HMO variable. This is an important step, given the large imbalance in the data) – used the R Caret Package

• Random Seeds were set for reproducibility

• Exploratory analysis was then undertaken to establish potential predictors.

• All exploratory analysis was undertaken only on the training set.
Here is the idea!

TRAINING SET
Exploratory data analysis

- Each Variable was tested individually between known HMO and non HMO properties
- The tests were undertaken on the training set only – to avoid overfitting
- Chi Squared test done on each for significance.
- Simple Mosaic Plots were used for visualising differences in factor variables
- Here are some of the key variables we ended up using in the models
Exploratory data analysis

Council Tax Reduction?

Not HMO

HMO

No Council tax Reduction

Council tax Reduction

Number of households

Pearson's Chi-squared test with Yates' continuity correction data: table(training$HMO, training$Ctax_Disc) X-squared = 67.776, df = 1, p-value < 2.2e-16
Exploratory data analysis

Receiving Housing Benefit?

Not HMO

HMO

No Housing Benefit

Housing Benefit

Number of households
Exploratory data analysis

Young people on School Census in household?

<table>
<thead>
<tr>
<th></th>
<th>Not HMO</th>
<th>HMO</th>
</tr>
</thead>
<tbody>
<tr>
<td>NO</td>
<td></td>
<td></td>
</tr>
<tr>
<td>YES</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Number of households
Exploratory data analysis

Large property: Council Tax band D or higher?

Number of households

Not HMO

HMO

NO

YES
Exploratory data analysis

Side Waste at Property?

Not HMO

HMO

NO

YES

Number of households
Exploratory data analysis

Anti Social Behaviour reports over previous 4 years

Number of households

Not HMO

HMO

NO

YES
Exploratory data analysis

We also used other predictors including

- Number of moves on electoral register between two points in time

- Number of Habitable Rooms: These were taken from Energy Performance certificate data available from MHCLG. Missing values were imputed from Council Tax band

- Most recent date property sold: Land Registry data

May add further geographical variables in the future, for example to define most likely parts of the borough to have private rented properties
Model Building

• Tree based algorithms were primarily used to build the models partly because there is no assumptions needed about normality of data nor the effect of covariance

• We did undertake multiple logistic regression, which had reasonable results, but feel the data may need to be transformed and more carefully chosen

• We used several models including:
  • Extreme Gradient Boosting (Xgboost)
  • Random Forest
  • Balanced Random Forest

• Each model was run via the R Caret package and was trained and checked using 10 fold cross validation, and some other tuning parameters, including tree size, tree number

• The models were built to include a probability score so optimal thresholds could be ascertained.

• Key aim in setting threshold was to balance the number of visits required by staff to find an HMO whilst maximising the number of households found
Example of a decision tree: Identifying Vampires

**Vampire?**

**Lives in a**

- **Semi detached, flat, bungalow**
  - **Avoids Garlic?**
    - **No**
    - **Yes**

- **Castle**
  - **Avoids Garlic?**
    - **No**
    - **Yes**

```markdown
Example of a decision tree: Identifying Vampires

**Vampire?**

**Lives in a**

- **Semi detached, flat, bungalow**
  - **Avoids Garlic?**
    - **No**
    - **Yes**

- **Castle**
  - **Avoids Garlic?**
    - **No**
    - **Yes**
```
Training Results: Standard Random Forest: 5000 trees

Random Forest 5000 trees

<table>
<thead>
<tr>
<th></th>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NOT HMO</td>
<td>HMO</td>
</tr>
<tr>
<td><strong>NOT</strong></td>
<td>2033</td>
<td>36</td>
</tr>
<tr>
<td><strong>HMO</strong></td>
<td>570</td>
<td>65</td>
</tr>
</tbody>
</table>

Precision: $\frac{65}{(65+570)} = 10\%$
Visit 10 households find one HMO

Recall: $\frac{65}{(65+36)} = 64\%$
Identify 64% of all HMOs
Training Results: XGBoost

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>NOT HMO</td>
<td>1852</td>
</tr>
<tr>
<td>HMO</td>
<td>18</td>
</tr>
<tr>
<td>NOT HMO</td>
<td>751</td>
</tr>
<tr>
<td>HMO</td>
<td>83</td>
</tr>
</tbody>
</table>

Precision: \( \frac{83}{83+751} = 10\% \)
Visit 10 households find one HMO

Recall: \( \frac{83}{83+18} = 82\% \)
Identify 82% of all HMOs
Training Results: Balanced Random Forest 5000 trees

Balanced Random Forest (Up-sampled)

<table>
<thead>
<tr>
<th></th>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>NOT HMO</td>
<td>2364</td>
<td>2364</td>
</tr>
<tr>
<td>HMO</td>
<td>18</td>
<td>83</td>
</tr>
</tbody>
</table>

Precision: $\frac{83}{(83+293)} = \frac{83}{376} \approx 22\%$

Visit 5 households find one HMO

Recall: $\frac{83}{(83+18)} = \frac{83}{101} \approx 82\%$

Identify 82% of all HMOs
## Training Results: Ensemble method

<table>
<thead>
<tr>
<th>Predicted</th>
<th>Actual</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>NOT HMO</td>
<td>2351</td>
<td>18</td>
<td></td>
</tr>
<tr>
<td>HMO</td>
<td>252</td>
<td>82</td>
<td></td>
</tr>
</tbody>
</table>

### Precision

\[ \text{Precision} = \frac{82}{82+252} = 25\% \]
Visit 4 households find one HMO

### Recall

\[ \text{Recall} = \frac{82}{82+18} = 82\% \]
Identify 82% of all HMOs
Real Results: Between October 2017 and March 2018

<table>
<thead>
<tr>
<th>Predicted</th>
<th>Actual</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>NOT HMO</td>
<td>NOT HMO</td>
<td>582</td>
</tr>
<tr>
<td>HMO</td>
<td>HMO</td>
<td>12</td>
</tr>
</tbody>
</table>

Precision: \( \frac{20}{20 + 87} = 17\% \)
Visit 6 households find one HMO

Recall: \( \frac{20}{20 + 12} = 62.5\% \)
Identify 62.5% of all HMOs
Results: Licences granted since October 2017

Percentage of predicted HMOs by Licence type granted

- Predicted HMO
- No
- Yes

Type of Licence granted
- HM1 (HSG) HMO Licensing
- HM2 (HSG) Discretionary Licensing
- HM5 (HSG) Additional Licensing
And the Punchline!!

Based on results so far

We have made improvements from this

To This

If we are lucky!!!
THANK YOU

ANY QUESTIONS?
London Office of Data Analytics
LODA pilot aims

- Test the policy or service impact of data science
- Show that data-sharing is possible and has tangible benefits
- Develop data sharing protocols useful for the longer term
- Identify barriers to collaborative working and develop solutions
- Contribute to the development of a culture of data-sharing within London
London Office of Data Analytics

a hub for the development, commissioning and implementation of data science projects aimed at addressing public services and urban challenges which are better tackled together, and which may affect more than one agency
Cambridge Analytica: The story so far

By Zoe Kleinman
Technology reporter, BBC News

21 March 2018

It's a sensational story containing allegations of sleaze, psychological manipulation and data misuse that has provoked an internationally furious response.

Tech giant Facebook and data analytics firm Cambridge Analytica are at the centre of a dispute over the harvesting and use of personal data - and whether it was used to influence the outcome of the US 2016 presidential election or the UK Brexit referendum.

Brexit: MPs warn of multiple obstacles to EU security deal

21 March 2018

A longer transition period after Brexit may be needed to guarantee continued security co-operation, MPs have said.
1. A catalogue of data sharing agreements
   - For a given dataset – who am I sharing it with (and under what terms)?
   - For a given organisation – what are we already sharing with them?

2. Create ‘high-level’ agreements between organisations
   - Signed off by Information Governance lead
   - Can be referenced by the individual data flows

3. Electronic signoff
   - Delegated authority

4. Organisation assurance
1. A catalogue of data sharing agreements
   • For a given dataset – who am I sharing it with (and under what terms)?
   • For a given organisation – what are we already sharing with them?

2. Create ‘high-level’ agreements between organisations
   • Signed off by Information Governance lead
   • Can be referenced by the individual data flows

3. Electronic signoff
   • Delegated authority

4. Organisation assurance
1. A catalogue of data sharing agreements
   • For a given dataset – who am I sharing it with (and under what terms)?
   • For a given organisation – what are we already sharing with them?

2. Create ‘high-level’ agreements between organisations
   • Signed off by Information Governance lead
   • Can be referenced by the individual data flows

3. Electronic signoff
   • Delegated authority

4. Organisation assurance

<table>
<thead>
<tr>
<th>Organisation Name</th>
<th>Single Lic</th>
<th>ICO Number</th>
<th>Category</th>
<th>Contact Email</th>
<th>Assurance</th>
<th>Admin Group</th>
<th>Lic</th>
<th>Setup %</th>
</tr>
</thead>
<tbody>
<tr>
<td>GREATER LONDON AUTHORITY</td>
<td>100%</td>
<td>Z4760661</td>
<td>Local Authority</td>
<td><a href="mailto:Paul.Hodgson@london.gov.uk">Paul.Hodgson@london.gov.uk</a></td>
<td>Significant</td>
<td>London Information Sharing Alliance</td>
<td>🟢</td>
<td>100%</td>
</tr>
<tr>
<td>LONDON FIRE &amp; EMERGENCY PLANNING AUTHORITY (LFPA)</td>
<td>100%</td>
<td>Z7122455</td>
<td>Fire Service</td>
<td><a href="mailto:andrew.mobbs@london-fire.gov.uk">andrew.mobbs@london-fire.gov.uk</a></td>
<td>Significant</td>
<td>London Information Sharing Alliance</td>
<td>🟢</td>
<td>100%</td>
</tr>
<tr>
<td>LONDON LEGACY DEVELOPMENT CORPORATION</td>
<td>100%</td>
<td>Z3138681</td>
<td>Local Authority</td>
<td><a href="mailto:DannyBudzak@londonlegacy.co.uk">DannyBudzak@londonlegacy.co.uk</a></td>
<td>Not submitted</td>
<td>London Information Sharing Alliance</td>
<td>🟢</td>
<td>57%</td>
</tr>
</tbody>
</table>
1. A catalogue of data sharing agreements
   - For a given dataset – who am I sharing it with (and under what terms)?
   - For a given organisation – what are we already sharing with them?

2. Create ‘high-level’ agreements between organisations
   - Signed off by Information Governance lead
   - Can be referenced by the individual data flows

3. Electronic signoff
   - Delegated authority

4. Organisation assurance

<table>
<thead>
<tr>
<th>Organisation Name</th>
<th>Single Lic</th>
<th>ICO Number</th>
<th>Category</th>
<th>Contact Email</th>
<th>Assurance</th>
<th>Admin Group</th>
<th>Lic</th>
<th>Setup %</th>
</tr>
</thead>
<tbody>
<tr>
<td>GREATER LONDON AUTHORITY</td>
<td>☑</td>
<td>Z4760661</td>
<td>Local Authority</td>
<td><a href="mailto:Paul.Hodgson@london.gov.uk">Paul.Hodgson@london.gov.uk</a></td>
<td>Significant</td>
<td>London Information Sharing Alliance</td>
<td>☑</td>
<td>100%</td>
</tr>
<tr>
<td>LONDON FIRE &amp; EMERGENCY PLANNING AUTHORITY (LFPA)</td>
<td>☑</td>
<td>Z7122455</td>
<td>Fire Service</td>
<td><a href="mailto:andrew.moobs@london-fire.gov.uk">andrew.moobs@london-fire.gov.uk</a></td>
<td>Significant</td>
<td>London Information Sharing Alliance</td>
<td>☑</td>
<td>86%</td>
</tr>
<tr>
<td>LONDON LEGACY DEVELOPMENT CORPORATION</td>
<td>☑</td>
<td>Z3138861</td>
<td>Local Authority</td>
<td><a href="mailto:Danny.Budzak@londonlegacy.co.uk">Danny.Budzak@londonlegacy.co.uk</a></td>
<td>Not submitted</td>
<td>London Information Sharing Alliance</td>
<td>☑</td>
<td>57%</td>
</tr>
</tbody>
</table>
5. Below each data sharing agreement, you can record individual ‘data flows’
- How are you transferring the data
- How are you storing it?
- For a given organisation – what are we already sharing with them?

<table>
<thead>
<tr>
<th>ISGID</th>
<th>Status</th>
<th>Summary Name</th>
<th>Data Flow Name / Identifier</th>
<th>Risk Rating</th>
<th>Added</th>
<th>First Signed</th>
<th>Export</th>
<th>Copy</th>
<th>Archive / Delete</th>
</tr>
</thead>
<tbody>
<tr>
<td>DF002687</td>
<td></td>
<td>PSMA data for contractors</td>
<td>OS AddressBase data to Energy Saving Trust</td>
<td>Not Assessed</td>
<td>23/01/2018</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DF002686</td>
<td></td>
<td>PSMA data for contractors</td>
<td>OS AddressBase data to RetrofitWorks</td>
<td>Not Assessed</td>
<td>23/01/2018</td>
<td>23/01/2018</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DF002690</td>
<td></td>
<td>SafeStats. LFB</td>
<td>GLA disclosure to LFB (via SafeStats)</td>
<td>Not Assessed</td>
<td>25/01/2018</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

6. GDPR
- ISG is ICO compliant and will be GDPR compliant
- Can use ISG to respond to requests such as “what are you doing with data about me?”
- Can carry out Privacy Impact assessment as part of setting up a data flow
5. Below each data sharing agreement, you can record individual ‘data flows’
   - How are you transferring the data
   - How are you storing it?
   - For a given organisation – what are we already sharing with them?

<table>
<thead>
<tr>
<th>ISGID</th>
<th>Status</th>
<th>Summary Name</th>
<th>Data Flow Name / Identifier</th>
<th>Risk Rating</th>
<th>Added</th>
<th>First Signed</th>
<th>Export</th>
<th>Copy</th>
<th>Archive / Delete</th>
</tr>
</thead>
<tbody>
<tr>
<td>DF002687</td>
<td></td>
<td>PSMA data for contractors</td>
<td>OS AddressBase data to Energy Saving Trust</td>
<td>Not Assessed</td>
<td>23/01/2018</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DF002686</td>
<td></td>
<td>PSMA data for contractors</td>
<td>OS AddressBase data to RetrofitWorks</td>
<td>Not Assessed</td>
<td>23/01/2018</td>
<td>23/01/2018</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DF002690</td>
<td></td>
<td>SafeStats. LFB</td>
<td>GLA disclosure to LFB (via SafeStats)</td>
<td>Not Assessed</td>
<td>25/01/2018</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

6. GDPR
   - ISG is ICO compliant and will be GDPR compliant
   - Can use ISG to respond to requests such as “what are you doing with data about me?”
   - Can carry out Privacy Impact assessment as part of setting up a data flow
7. **Organisations**
   - 100 initial licences
   - Full use of ISG
   - Generally defined as an entity that has its own Information Governance set up

8. **Sponsored Organisations**
   - Unlimited
   - Can only ISG to share data with the sponsoring organisation – sign up to data sharing
   - Smaller organisations (e.g. schools, community groups, etc)
There will never be a single warehouse for all of London’s data, so we need to connect.

Principles:
- Open Source
- Cloud-based
- Open APIs
- Sharing knowledge with other cities

- secure sharing of catalogues &/or data
Data Science questions (in approximate order of difficulty):

- **Descriptive** (can’t be generalised)
- **Exploratory** (discover new connections, define future studies)
- **Inferential** (estimate a quantity & uncertainty – e.g. opinion surveys)
- **Predictive** (link not cause – e.g. people who buy lots of strong mints have a higher risk of cancer)
- **Causal** (needs subject knowledge, probably only show average effects e.g. on a neighbourhood rather than a particular household)
- **Mechanistic** (scientific or engineering systems – not applicable to GLA work)
Data Science questions
(in approximate order of difficulty):

- **Descriptive** (can’t be generalised)
- **Exploratory** (discover new connections, define future studies)
- **Inferential** (estimate a quantity & uncertainty – e.g. opinion surveys)
- **Predictive** (link not cause – e.g. people who buy lots of strong mints have a higher risk of cancer)
- **Causal** (needs subject knowledge, probably only show average effects e.g. on a neighbourhood rather than a particular household)
- **Mechanistic** (scientific or engineering systems – not applicable to GLA work)
With thanks to

- **Data for Service Improvement**
- **Data for Better Decision Making and Policy**
- **Urban Experimentation**
What next?

1. Project Development Board
2. Information Governance Officer (jointly with LfB)
3. Further developments to City DataStore
4. Use London DataStore – resources, data academy, communication

- 1st year of operations
Paul Hodgson
GIS & Infrastructure Manager
Greater London Authority
City Hall
The Queen’s Walk
London SE1 2AA
paul.hodgson@london.gov.uk
data.london.gov.uk