BIRKBECK, UNIVERSITY OF LONDON

MSc PROJECT REPORT

Mapping London House Prices through Well-being

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A project report submitted in fulfilment of the requirements for the degree of Master of Science

in the

Department of Computer Science and Information Systems

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Declaration of Authorship

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BIRKBECK, UNIVERSITY OF LONDON

Abstract

School of Business, Economics and Informatics
Department of Computer Science and Information Systems

Master of Science

Mapping London House Prices through Well-being

by Ben CANDY

I have always been interested in the spatial analysis of human behaviour. For this project I am going to put together a software project which will allow me to visualise this in a data-driven way. In my literature review I discovered that there are hardly any quantifiable metrics to link human happiness a real estate values in a geographical context. Therefore, I look forward to experimenting with new measures, trying to leverage the wealth of data we now have on "London Living" and Data Science methods such as Principal component analysis and dimensionality reduction.

Acknowledgements

I would like to thank my project supervisor Professor Alessandro Provetti for his support and guidance throughout this project...

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Chapter 1

Introduction

1.1 Motivations and problem statement

In recent years, the concept of well-being has been the subject of increasing interests for governments, councils, policy makers and researchers, though research on the subject has been happening since the 1970s. An interesting recent development is a report into well-being in Danish cities by (OECD, 2016) which highlights how well-being tools have become an important tool to identify the needs of citizens and the domains where demand for progress is greatest.

This idea of well-being is often defined using a set of indicators relating to a particular place. There is no universally agreed definition of exactly which factors are the best measures of well-being, however, various indexes and studies show a great deal of commonality on the types of measures that are important to the well-being of citizens.

What is less clear is whether, and how, these indicators affect the real estate values in a specific city. For example, The Greater London Authority created a set of well-being indicators and used them to create a map of well-being by London Ward in 2014 (GLA, 2014), however, this was not linked back to real estate values. In one study looking at linkages between house prices and mental wellbeing, (Ratcliffe, 2013), points out that when people can move freely, each person will maximize well-being by moving to areas that best satisfy their preferences; this results in zero correlation between area characteristics (or house prices) and wellbeing. But if people think they are paying too much for poor quality or too little for high quality, we would observe a positive relationship between area characteristics and wellbeing. The study found a positive correlation between house prices and mental wellbeing.

Another hypothesis found in the Economics literature is that real estate values are the drivers of the well-being indicators, happier people are better at generating wealth (Lyubomirsky, King, and Diener, 2005), which leaves open the possibility that areas with high well-being provide a flow of people migrating to places with higher real estate values. From the point of view of Data Science it would be interesting to consider the real estate values in bandings such as quintiles as well-being indicators may have a very different relationship with the top 20 percent of areas by real estate value than with areas in the lower four quintiles.

Work on urban scaling (Bettencourt et al., 2010) suggests that different types of well-being indicators may have different relationships with real estate values due to the non-linear nature of agglomeration. Bettencourt et al. argues that city indicators are governed by power laws rather than linear per-capita indicators. Social factors tend to be superlinear whereas material infrastructure tends to be sublinear at best. There may therefore be some level of divergence between different well-being factors. This project focuses on the city of London and tries to determine which well-being indicators show a relationship with real-estate values. The findings will be

displayed in the form of an interactive map.

This project sets out to create a set of well-being indicators for each administrative ward in London and will attempt to model median house prices based on these indicators.

1.2 Project trailer

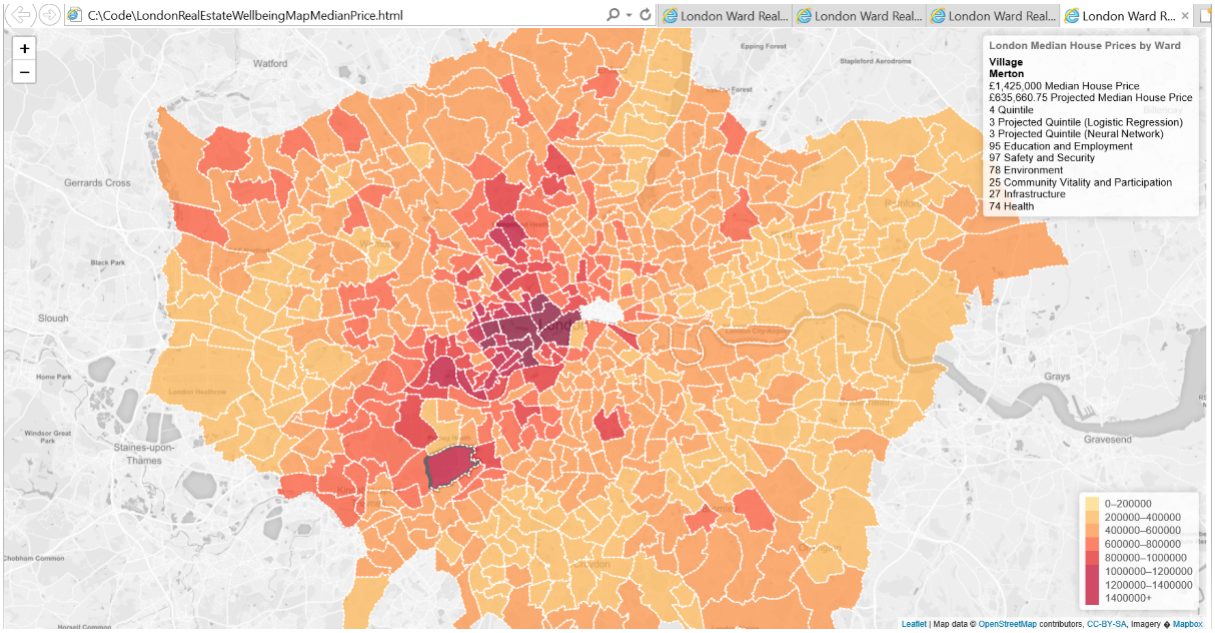


FIGURE 1.1: Visualisation of median house prices by ward in London. Hovering over a particular ward will provide information on the well-being indices for that ward and the modelled median house prices and associated quintiles.

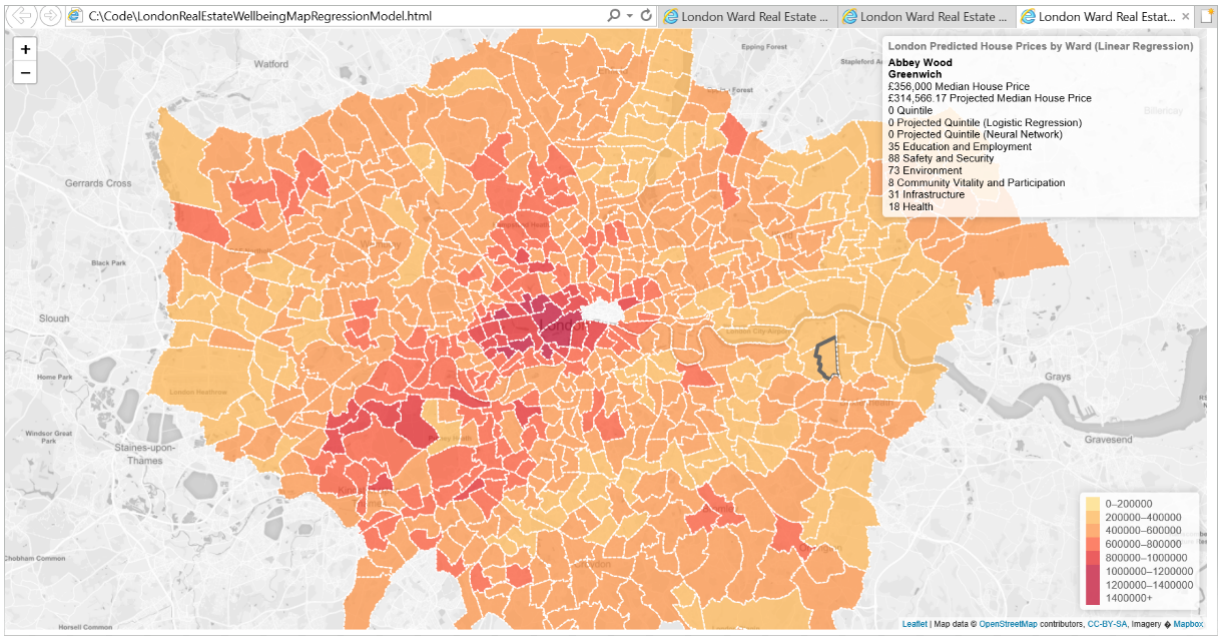


FIGURE 1.2: Visualisation of predicted median house prices by ward in London. This map shows the predicted values based on a linear regression model.

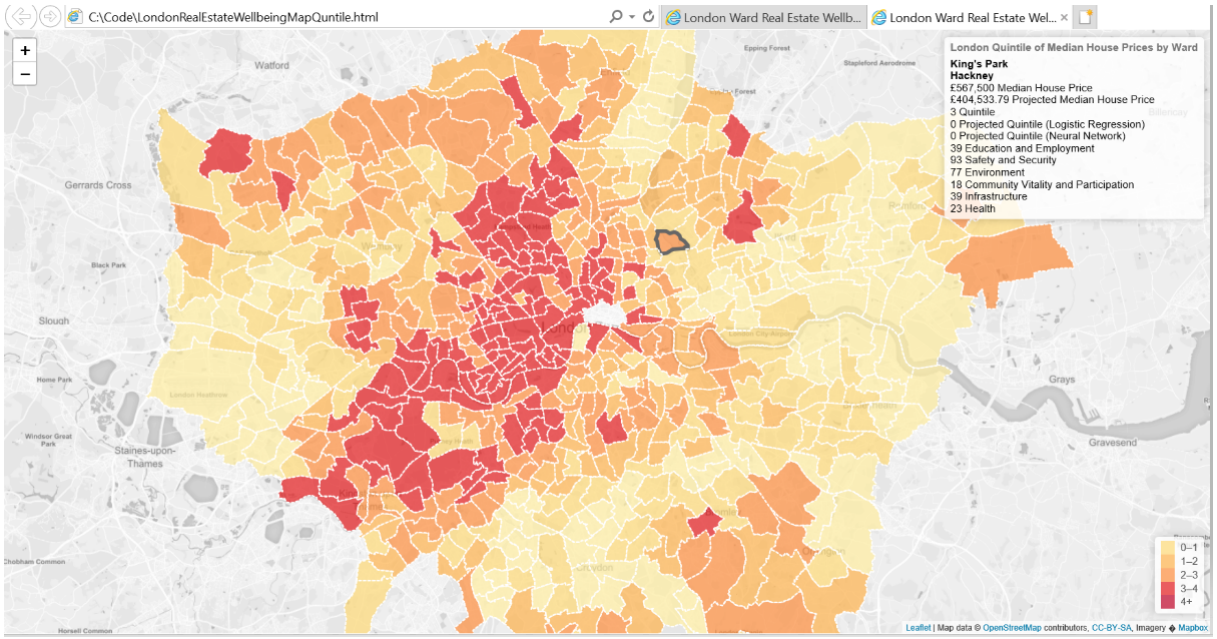


FIGURE 1.3: Visualisation of the quintiles of median house prices by ward in London. Hovering over a particular ward will provide information on the well-being indices for that ward and the modelled median house prices and associated quintiles.

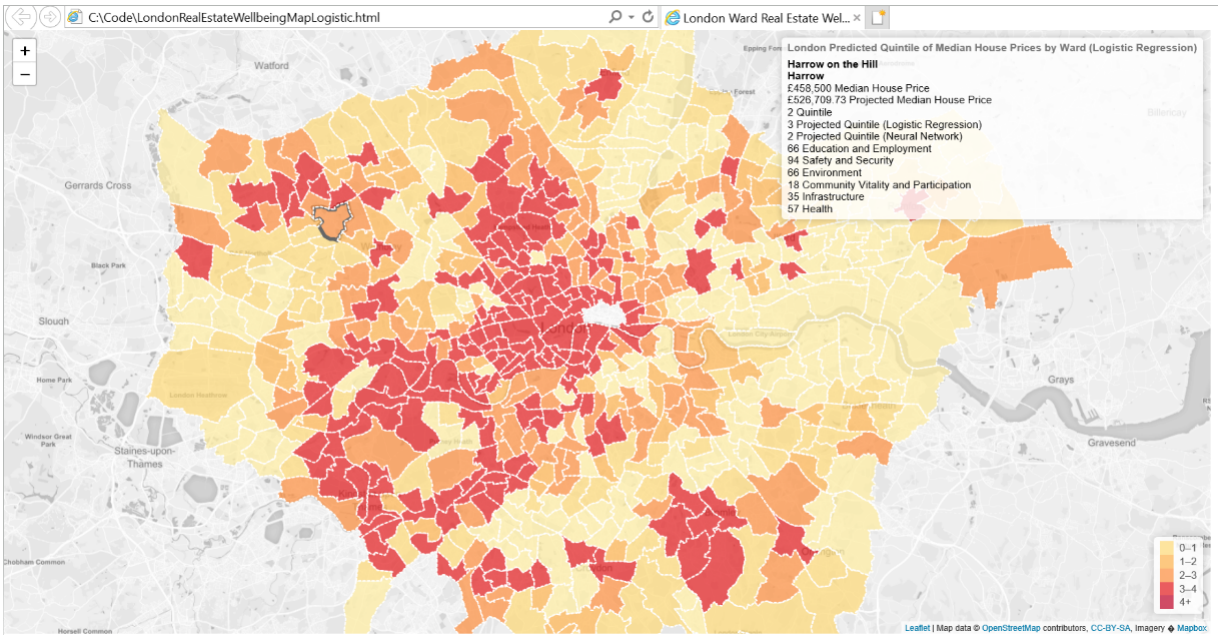


FIGURE 1.4: Visualisation of the predicted quintiles median house prices by ward in London. This map shows the predicted values based on a logistic regression model.

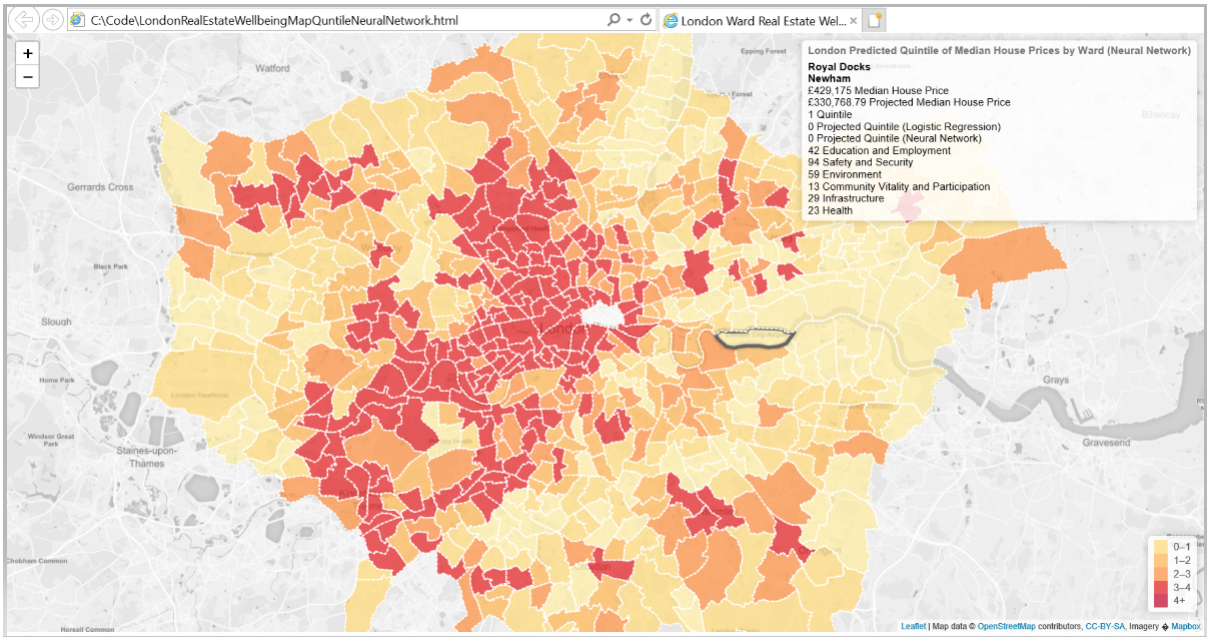


FIGURE 1.5: Visualisation of the predicted quintiles median house prices by ward in London. This map shows the predicted values based on a neural network.

Chapter 2

State of the art

2.1 Geospatial analysis in Data Science

Maps are an increasingly popular way to visualise data where some form of geographic aspect is an important element of the analysis. The website London Mapping (MappingLondon.co.uk, 2018) is a good example of the large amount of data analysis and visualisation taking place through the creation of various types of map for the city of London alone.

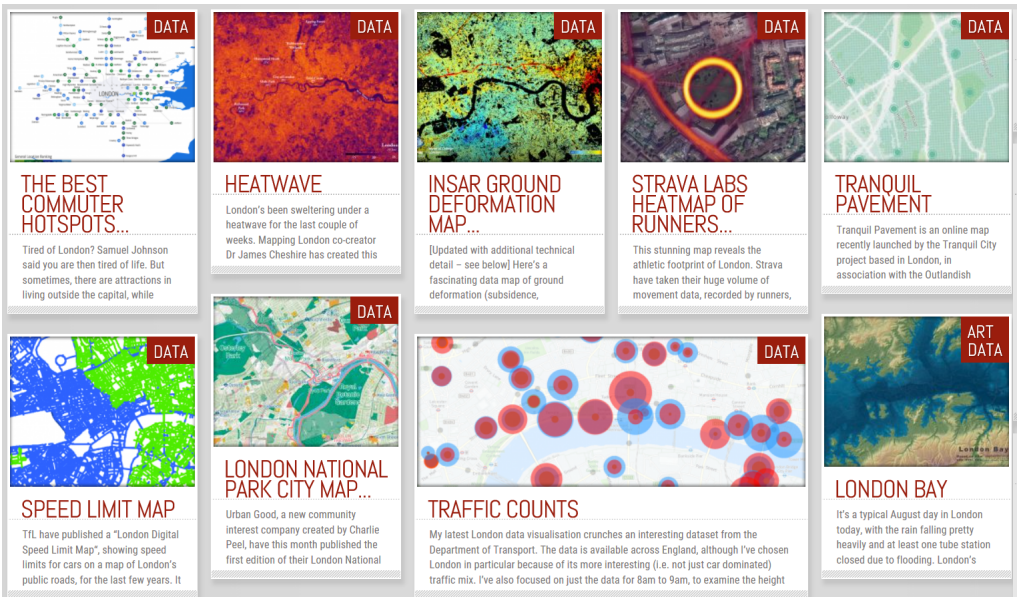


FIGURE 2.1: An range of the maps exploring London on the Mapping London website. This website has been created by academics from the geography department at UCL and features a range of data-driven maps using various geospatial techniques.

There are several reasons why maps are a good choice for data visualisation which include:

- They provide a real-world context for the data, helping the audience to understand the analysis
- They allow users to compare data over different areas or regions at a glance

Data Science techniques play an important role in the creation of this kind of visualisation. Most map visualisations represent locations through coordinate reference systems which represent locations. These locations can be specific locations

represented by pairs of coordinates, most often (latitude, longitude), or areas which would be represented by polygons consisting of multiple coordinate pairs. Data Science techniques are required to design functions and algorithms to map, aggregate or disaggregate data between different types of geometry and different coordinate reference systems.

2.1.1 Point Maps

One mapping technique often used in interactive visualisations would be a point map where specific instances of something are plotted as points in the geo-location in which they occur. This form of mapping would use a coordinate pair, often latitude and longitude but potentially an Ordnance Survey grid reference or other coordinate reference system. An example of this would be the Great British Public Toilet Map (RCA, 2014)

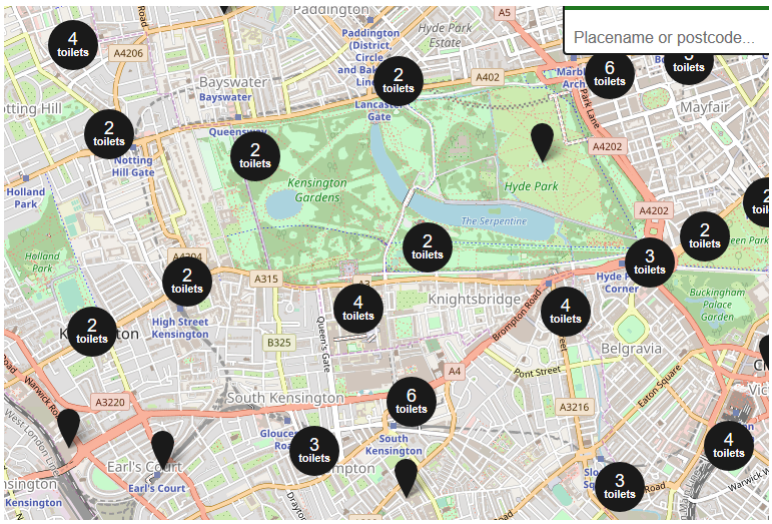


FIGURE 2.2: An example of a point map - the Great British Public Toilet map created by the Royal College of Art in 2014 showing instances of public lavatories across the country.

2.1.2 Choropleth Maps

The city of Toronto is a good example of where an informative interactive well-being map has been created (Toronto, 2018). On this map a user can click on an area and is presented with a panel showing the values for a number of measures.

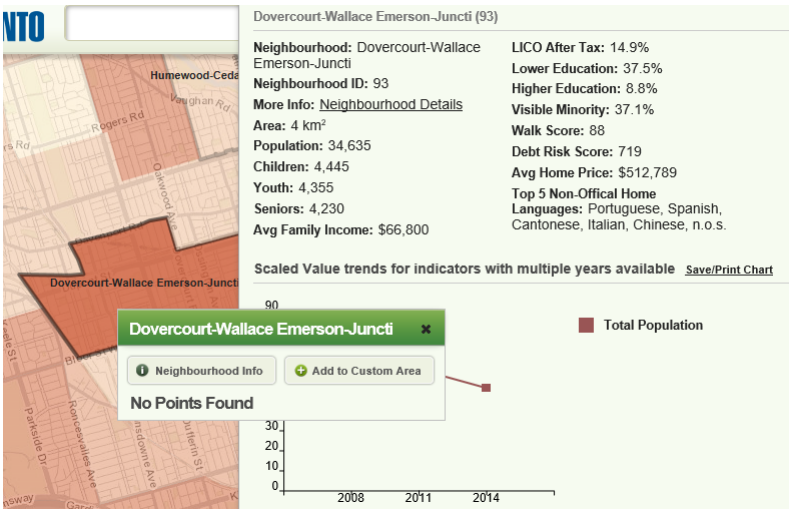


FIGURE 2.3: An example of a choropleth map - created by the City of Toronto to provide information about the neighbourhoods of urban Toronto.

The Toronto map uses a thematic mapping technique known as a Choropleth map, using shape files where polygons represent an area of space, in this instance neighbourhoods, with the colour of the polygon related to the value of the area in question. This map is an excellent design example for this project as the geometries used, in this case neighbourhoods of Toronto, are of a similar geospatial representation to London Wards. The project map will be based on median house prices and hovering over an area will display the values of the well-being indicators and the projected values of the model.

2.1.3 Heat Maps

Real estate values have also been an area of interest for mapping. In recent times these visual displays of real estate value have often been created by the commercial sector, for example, UK property price maps created by the estate agent Zoopla (Zoopla, 2018). This is an example of a heat map. Heat maps share similarities with Choropleth maps in that they assign a colour to an area based on the magnitude of a particular value. Where these two types of map differ is that heat maps assign colour to a cluster of connected points whereas for Choropleth maps, the colouration is based on a value for a polygon representing a given area, usually a administrative or political boundary.

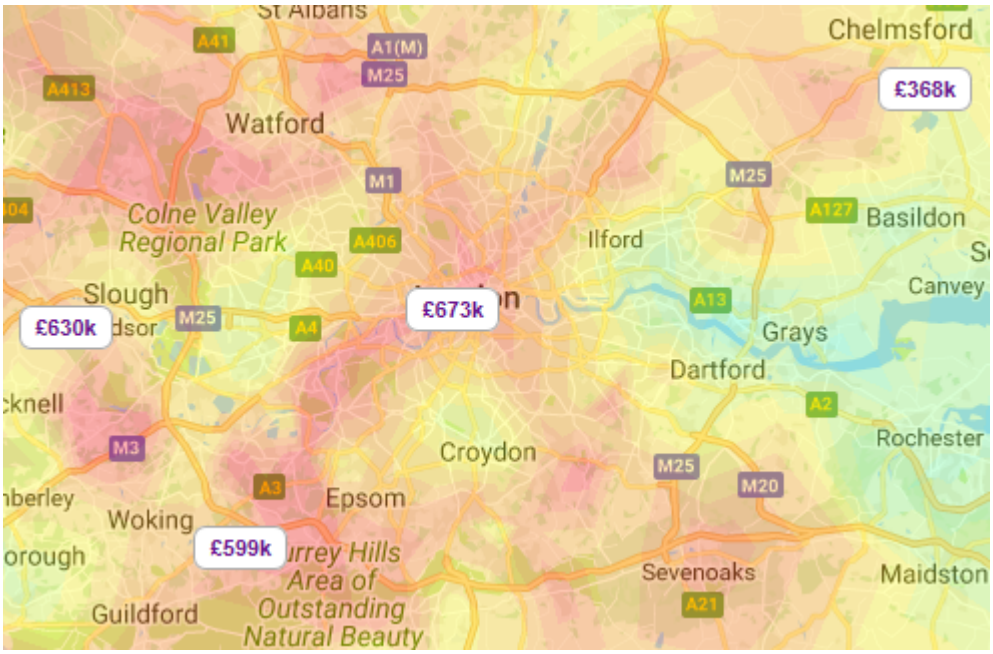


FIGURE 2.4: An example of a heat map - a 2011 map created by the estate agents Zoopla to show UK average house prices.

2.1.4 Network Maps

An interesting alternative approach has been taken by (Quercia, Aiello, and Schifanella, 2016) who have created a series of interactive maps using crowdsourced data and image processing techniques. The locations used in the maps created by Quercia et al. use specific locations represented by images and sound recordings rather than areas of space. Here, rather than using traditional spatial analysis techniques, the maps have been created using graphs which represent London as a network. The location of the images/sounds are the nodes and the routes between them form the vertices.

FIGURE 2.5: An example of a network map - created by Quercia, Aiello and Schifanello in 2016, this map categorises each road in London based on the primary type of noise heard in the location.

Chapter 3

Data Sources

3.1 Datasets required to create the well-being indices

To create the well-being indices the decision was made to use six indices each made up of three indicator datasets. For the purpose of the project, each index and indicator will be of equal weighting. This approach is based upon other indices of well-being where data feeds into a set of between five and ten indices. Three examples of this type of index would be the Gross National Happiness index (Bhutan Studies, 2011), the OECD Better Life Initiative (OECD, 2017) and the Canadian Index of Wellbeing (Waterloo, 2017). The approach taken was to find three indicators that both represented each index and where the data could be retrieved or transformed to be analysed at ward level.

TABLE 3.1: Indices and indicators used for the measurement of well-being for each London ward with data source and metric used

Index	Indicators	Source	Metric
Education and Employment	Average GCSE points	London Datastore	Average GCSE capped point score
	Average Ofsted rating of schools	edubase @ gov.uk	Average Ofsted ratings of schools - most recent inspections (September 2018)
	Employment rates	London Datastore	Rate of economically active individuals (2011)
Safety and Security	Crime rates - against the person	London Datastore	Number of recorded crimes (2017)
	Crime rates - other crime	London Datastore	Number of recorded crimes (2017)
	Traffic injuries	London Datastore	Road collision numbers (2014)
Environment	Air pollution	London Datastore	Annual mean of Nitrogen Dioxide (NO2) and Particle emissions (PM10) (2011)
	Amount of greenspace	London Datastore	Percentage of ward area which is greenspace (2011)
	Access to nature	London Datastore	Percentage of residential households with access to at least one open space (2011)
Community Vitality and Participation	Access to cultural space	Foursquare	Number of cultural venues in ward (August 2018)
	Amount of bars and restaurants	Foursquare	Number of bars and restaurants in ward (August 2018)
	Election turnout	London Datastore	Percentage of residents voting in 2016 London election
Infrastructure	Access to public transport	London Datastore	Transport for London Public Transport Accessibility Levels (2015)
	Average journey times	gov.uk	The mean percentage value of those within an hour's travel by public transport or walking of an area of 100, 500 and 500 jobs (2014)
	Population density	London Datastore	Persons per square km (2013)
Health	Life expectancy	London Datastore	Life expectancy at birth (2013)
	Childhood obesity	London Datastore	Prevalence of obese children at age 11 (2013)
	Illness preventing employment	gov.uk	Comparative illness and disability ratio from English Indices of Deprivation (2015)

Access to open space definition [1]
Access to public transport definition [2]
Illness preventing employment definition [3]

3.2 Static data files

The majority of data sets are either csv or Excel files which are accessed directly via a url by the data importer application. These sources are primarily from the websites of public bodies. The data importer application makes use of the pandas module within Python to support the importing and cleaning process within a series of dataframe objects.

[1] https://data.london.gov.uk/dataset/access-public-open-space-and-nature-ward
[2] https://data.london.gov.uk/dataset/public-transport-accessibility-levels
[3] https://www.gov.uk/government/statistics/english-indices-of-deprivation-2015

3.2.1 London Datastore

The Greater London Authority Datastore (GLA, 2018) was the primary source of data for the project with significant amounts of data relating to various London metrics available. The fact that much of the data contained on the website was available at ward level was key in being able to piece together the indices.

3.2.2 gov.uk

Used for Ofsted ratings for schools, average journey times and illness affecting employment, the gov.uk website contains a varied range of datasets. Three key datasets used from this source are the Edubase schools information for Ofsted ratings, 2014 Department for Transport journey time statistics and 2015 English Indices of deprivation. Without the London focus of the GLA Datastore, information on gov.uk is often harder to locate and in many cases is at a higher level of aggregation than required with most information at borough or national level.

3.2.3 esri

Data for average journey times and illness affecting employment was obtained at lower super output area, a lower level of aggregation than ward. The different geographical level used in the two datasets created the need for a mapping. The open data section of esri's ArcGIS website (esri, 2017) offered this mapping document in csv format which could be incorporated into the data import software to allow an arithmetic mean to be determined at ward level.

3.3 APIs

A subset of London data is also available via various APIs. For transport information Transport for London have extensive APIs available, unfortunately none of these were able to provide any of the datasets required for the project, though other formats offered by TFL were used. The use of APIs became focussed on collecting information on venues to obtain the data for the 'community vitality' and 'access to cultural spaces' datasets. For this data Foursquare was the primary candidate with venue information available with no cost implications.

3.3.1 Foursquare

Foursquare is a social media platform based on location intelligence. The platform has information on more than 105 million locations mapped worldwide and over 50 million users per month. (Foursquare, 2018). With the extensive database of venues with location information, Foursquare could be used to look at two of the indicators which feed into the Community Vitality and Participation index:

- Access to cultural spaces
- Popularity of bars and restaurants

To measure these two indicators, Foursquare's venue API can be used to return list of venues within a radius of a specific point provided in latitude and longitude. By using the three venue types, "culture", "food" and "nightlife", a list of venues fitting those types can be captured via the API. In the implementation phase, the list of

venues containing the point location of the venues can be mapped to the relevant ward and numbers aggregated to give an indicator of volume with which to measure this category.

3.3.2 Google Maps

The places API from Google Maps was queried and code written to extract venue data. However, after obtaining some basic search results it was decided that Google's pricing policy and rate limits made this data source unfeasible for the scope of the project.

3.4 Shape Files

For choropleth mapping, shape files are needed to visualise the polygon shapes which define administrative or political boundaries. Shape files usually consist of properties of the shape such as name and size along with a geometry feature which defines the boundaries of a given shape via the coordinates of their vertices. For this project, the relevant shapefile is key to creating the final interactive map and will also be use to visualise the data and support the model building process.

3.4.1 London Ward shapefile

The key shapefile for the project is taken from the London Datastore and provides the polygon geometry of the London wards. This is a .shp file where the point coordinates which make up the polygon for each ward are in the Ordnance Survey grid reference coordinate reference system. With point geometries more often listed in latitude and longitude, there will need to be some re-projection of coordinates to enable certain datasets to match with the shapefile.

3.5 Data availability issues

In part thanks to the Greater London Authority's Datastore, a wealth of information is available at London Ward level. Combining this with information from the Foursquare API and Department for Education schools data provided a significant body of information in which to model London as a multiple dataset. Data availability was such that datasets for each of the indicators feeding into the six indices were available and it was not necessary to use substitute indicators that differed significantly from those originally planned.

3.5.1 Timeliness

Some of the datasets related to different years, often linked to census years and administrative or electoral changes. Wherever possible the most recent data has been used to synchronise as closely as possible with the 2017 data used for the median house price data. For example, Emission data is from 2011 as this is the most recently published at ward level. The London Air Quality daily feed run by King's College does not have enough coverage to sufficiently differentiate over 600 wards. Ideally this data would have been from the same year as the house price information.

3.5.2 Boundary changes

Ward boundaries were re-drawn in three London Boroughs in 2014 meaning that a function had to be written that, for data pre-dating 2014, would map old ward codes to the new ward that contained the largest section of the newly defined area. Newer data would also have been helpful here but the commonality of area between the old and new codes in the mapping should ensure that the data is representative of the new area.

3.5.3 API rate limits

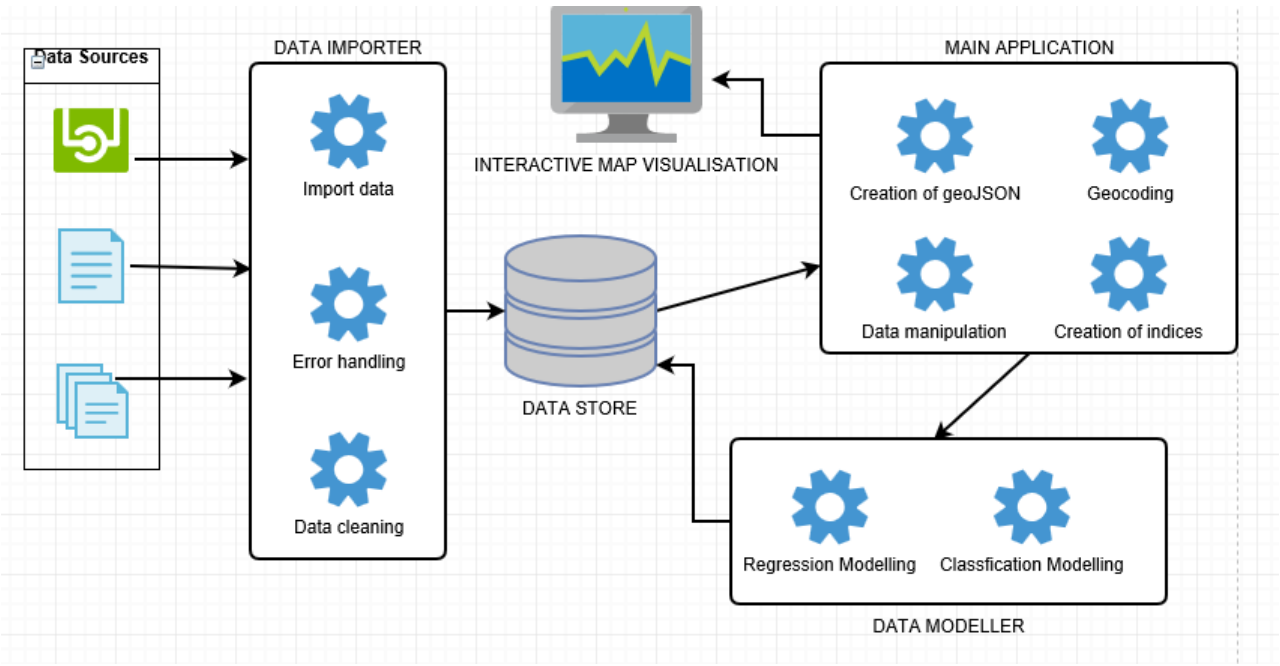
API limits and costs imposed limits on the depth of information that could be obtained from these sources. Whilst I was able to obtain the necessary Foursquare venue and venue location information, venue ratings and check-ins were subject to stringent daily limits which meant that obtaining this information would have taken weeks of daily iterations or significant costs neither of which were feasible for this project. I investigated the possibility of using Google Places API but the new pricing model introduced this year also made this unfeasible. In a commercial setting it may be possible to increase the amount of data that can be obtained from some of the APIs.

Chapter 4

Design

4.1 Architecture of the specification

4.1.1 Architecture diagram



4.1.2 Architecture choices

For this project two main technologies are being used, Python and JavaScript. The majority of the software code has been written in Python, specifically for the data import processes, for the main application which runs the analysis and geocoding and the data modelling component. Python was chosen for these components for a number of factors. Firstly for the data importer, Python has excellent capabilities for data processing allowing the data to be collected and cleaned leveraging the Pandas module. For the main application, Python's geocoding and spatial capabilities were important factors in the choice. The ability to import shape files and re-project coordinate systems leveraging Geopandas and Shapely allowed more flexibility in which datasets were suitable for the project and the option to export to geoJSON format facilitated the data visualisation. For the visualisation stages JavaScript embedded in a html file was chosen. For this final component of the project JavaScript was preferred to Python due to the interactive element required on the map. With the aid of the Leaflet.js package in JavaScript I was able to make use of more map features to present any end users with a more complete user experience.

4.2 Components

The software architecture design for the project has been created with the aim of being able to isolate individual elements in the interest of performance. The system is not dependent on processing a live data feed so it is important that the component that imports the data does not have to run every time a user would wish to access the interactive map visualisation. The design means that each component can be modified without affecting the other parts.

4.2.1 Data inputs

The data input layer is the base layer of the system. This consists of several different types of input including API feeds from the Foursquare platform, csv files collected directly from urls and other data files which have been pre-collected and loaded into the data store. This layer is the most likely to change moving forward as new and updated data sources are published or become available in alternative formats.

4.2.2 Data importer

The data importer software is written in Python and is designed as a series of functions. Each function imports one of the required datasets. Setting these up as separate functions gives the option to run imports individually. This is an important requirement of the system as certain imports take a considerable amount of time. The iterative nature of the API imports combined with daily rate limits mean that it is only feasible to run the API imports from Foursquare on at most a daily basis. As the system is not reliant on a live feed, the data import software could be run as an overnight batch process.

4.2.3 Data store

The data store is central to the architecture to safeguard performance levels. As the data imports are best suited to a batch process, the cleaned data files should be stored in the data store for the main application software to run efficiently. The data store is also used for any pre-collected data which cannot be collected directly from a url or API. This imports the data for the 18 base indicators which create the 6 well-being indices.

4.2.4 Main application

The main application software performs a variety of tasks and is written in Python. The first task that the software performs is to take the data that has been imported for the 18 base indicators from the data store. The main application then performs any data manipulation and applies a set of geocoding and spatial functions to standardise the data into a format where everything is aggregated for London Ward geometry. Having standardised, the software then creates the 6 well-being indices using functions drawing on Principal Component Analysis and mean calculation functions which also normalise the data to ensure that each score is between 0 and 100. These 6 indices are then combined with data showing median house prices and the related quintiles and passed through the regression and classification models chosen through the data modeller component. The final task performed by this component is to create a geoJSON file including the well-being index scores, median

house price information, spatial data and predicted regression and classification values. This file contains the data used in the visualisation.

4.2.5 Data modeller

The data modeller is a Python application which takes the data containing the 6 well-being indices and uses a range of modelling techniques to try and obtain the best model for the data. This is not an automated process which chooses the best score because interpretability is also a strong point of interest for this particular problem. The data modeller outputs the predicted values for the chosen model and returns them to the dataset for further use in the main application and in the interactive map. The data modeller is currently designed so that the solution developer would select the final models to be used in the map.

4.2.6 Interactive map

The final component of the software architecture is the interactive map which is built in JavaScript and html. This component builds a framework for the map using tiles from the MapBox service. A JavaScript function then takes the geoJSON file and adds this as a layer to the map. This part of the architecture can be seen as the user front end as the visualisation allows users to hover over each ward to see the scores, actuals and predictions along with features such as a zoom facility.

4.3 London house prices as a regression problem

London is known for having very high real estate values but we can see from the map below that there are specific wards, particularly in the western central area, where median house prices are significantly above the Greater London area as a whole.

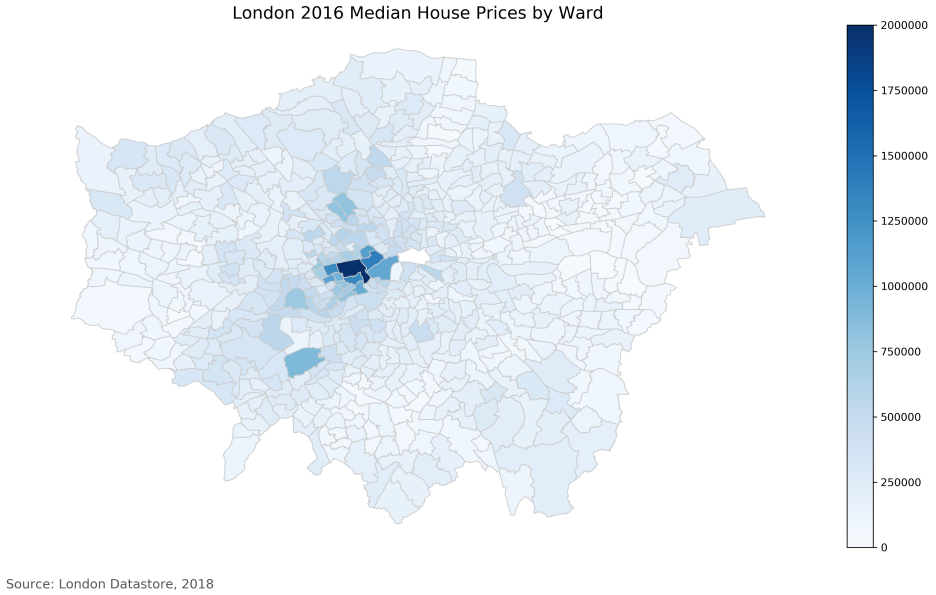


FIGURE 4.1: Choropleth map showing median house prices for each ward in London (based on values at the end of 2017).

The choropleth map would suggest a high number of wards fall at the lower end of the range of median house prices with a small number with significantly high prices. From the pairwise plot below, the shape of the histogram of median house prices by ward would suggest that a power law may best describe the distribution.

$$p(x) = x^{-4.314410441437625} \tag{4.1}$$

For the indices, the histograms show most of the six as being at least close to a normal distribution. This is less clear in the case of the Safety and Security and Community Vitality and Participation indices with Safety and Security showing a large number of high values and Community Vitality and Participation showing many low scores. This can be attributed to a small number of wards where crime is high and that wards in central London have much greater access to both cultural and social spaces as indicated on the maps below. In both cases, a power law may best describe these distributions.

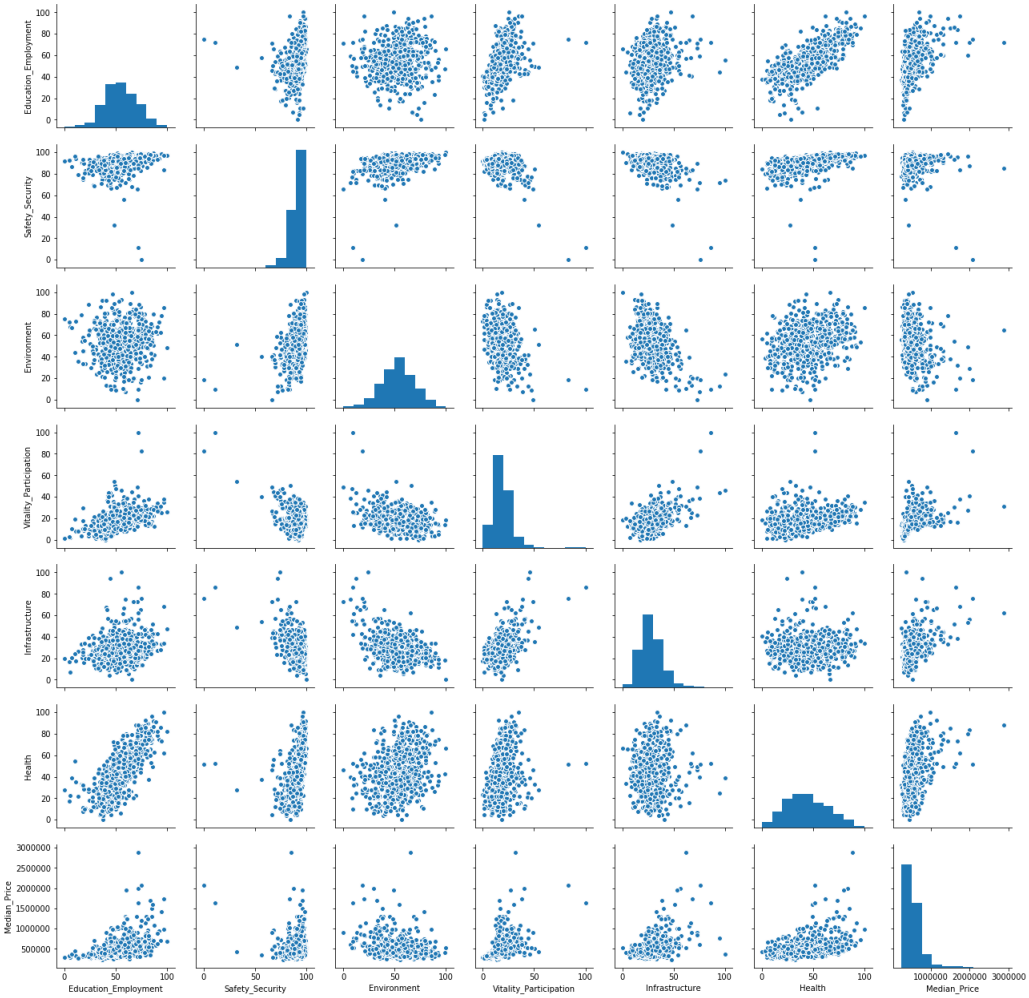


FIGURE 4.2: Pair-wise plot of the six well-being indices London median house prices with histograms showing the distribution of each index and house prices.

This is less clear in the case of the Safety and Security and Community Vitality and Participation indices with Safety and Security showing a large number of high values and Community Vitality and Participation showing many low scores. This can be attributed to a small number of wards where crime is high and that wards in central London have much greater access to both cultural and social spaces as indicated on the maps below. In both cases, a power law may best describe these distributions.

TABLE 4.1: Correlation Matrix for the six indices and median house prices (000s)

Correlation Matrix	Education and Employment	Safety and Security	Environment	Vitality and Participation	Infrastructure	Health	Median House Price
Education and Employment	1	0.246739481	0.078228197	0.422030673	-0.050583652	0.746026055	0.447882095
Safety and Security	0.246739481	1	0.394489799	-0.462644114	-0.418567441	0.382769813	-0.154480959
Environment	0.078228197	0.394489799	1	-0.280237241	-0.781988848	0.306477755	-0.249970294
Vitality and Participation	0.422030673	-0.462644114	-0.280237241	1	0.366691459	0.261488702	0.494699468
Infrastructure	-0.050583652	-0.418567441	-0.781988848	0.366691459	1	-0.342914525	0.404117458
Health	0.746026055	0.382769813	0.306477755	0.261488702	-0.342914525	1	0.376834435
Median House Price	0.447882095	-0.154480959	-0.249970294	0.494699468	0.404117458	0.376834435	1

The indices show a mixture of levels of correlation with each other. Environment

and Infrastructure have a strong negative correlation, possibly because a central location generally has a high Infrastructure score with more transport options and shorter journey times, whereas Environment scores better in Outer London where congestion is lower. The strongest correlation is between Health and Education and Employment.

4.4 London house prices as a classification problem

The choropleth map below shows a different picture of London house prices being based on quintiles rather than monetary values, here the fifth quintile covers a larger range of values than the other quintiles due to the extremely expensive areas such as Knightsbridge and Belgravia where the median house price reaches over £2.8 million, 10 times as much as North End ward in Bexley.

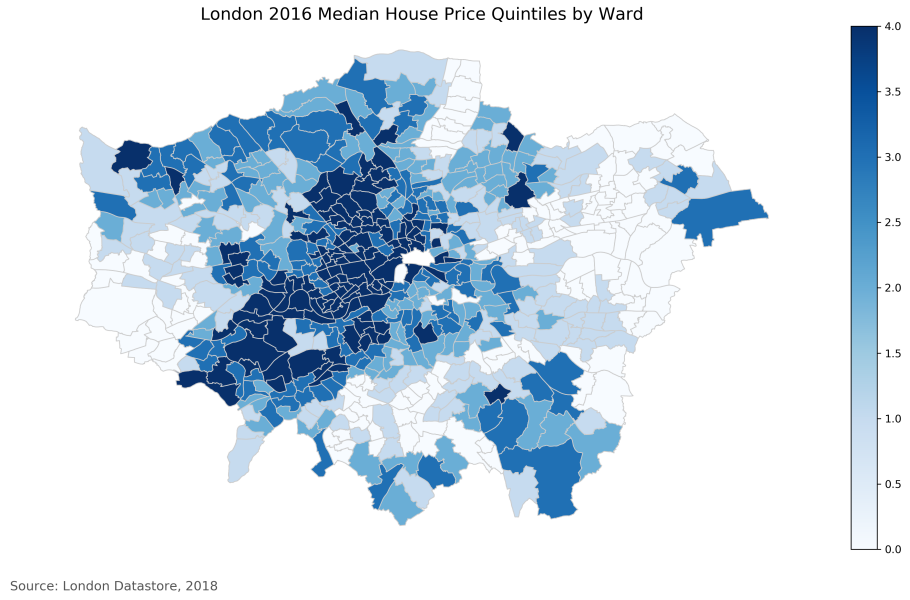


FIGURE 4.3: Choropleth map showing median house prices by for each ward in London by quintile (based on values at the end of 2017).

For the classification problem the aim was to try to find a model that has both a good fit and high interpretability. However, models that often have high accuracy but low interpretability such as neural networks were also used to both discover and validate the best classification model for the problem.

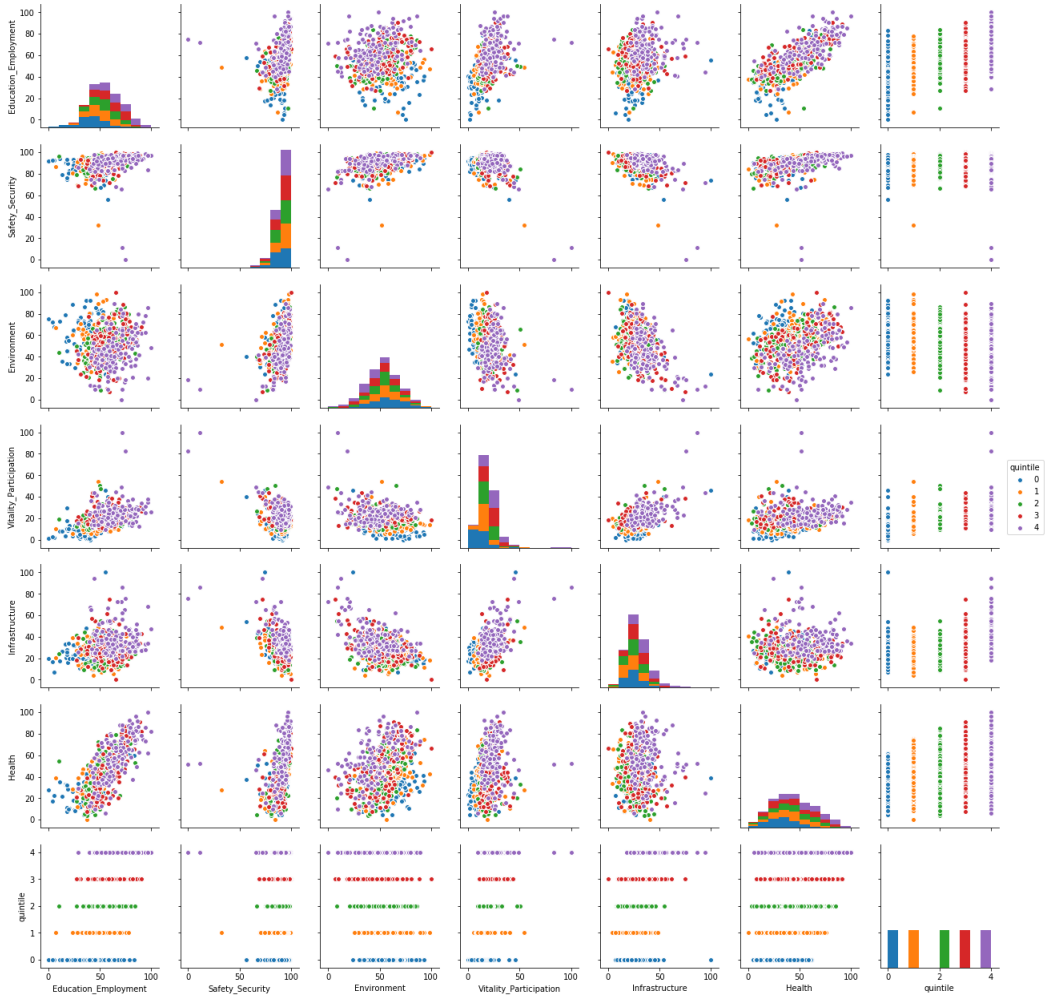


FIGURE 4.4: Pair-wise plot of the six well-being indices London median house prices with histograms showing the distribution of each index and house prices. Points are coloured on the basis of the quintile of the median house price within London ward.

By using the pair-wise plot and colouring the points by quintile, it is clear that there is no clear separation of quintile for any of the indices with a more gradual movement from first to fifth quintile for most indices. Environment and Safety and Security have an almost inverse relationship with the quintiles. Because the majority of the high-priced wards are centrally located, this may relate to a lack of greenspace and higher pollution centrally as well as providing high-value targets for crime.

Chapter 5

Implementation

5.1 Data collection and cleaning

The key foundation of the project was being able to collect the data that would allow the creation of the well-being domain scores. Collecting the required data and shaping it into the formats that were needed was, in places, one of the most challenging aspects of the project and the one that required the largest proportion of time. This part of the project presented several challenges that needed to be overcome.

5.1.1 Collection of data files

For ward level data, the Greater London Authority's Datastore is a primary data source. A significant proportion of the data for the creating of the well-being indicators could be accessed via this source.

5.1.2 Collection from APIs

The API that was key to the success of the project was that of social media platform Foursquare. To represent community vitality, the aim was to create a measure for the restaurants and bars in each ward. Foursquare is a platform based around venue information so holds the information required for this measure. Foursquare also holds information on cultural venues. Therefore the measure of 'Access to Cultural Space' could also be obtained from this platform. To use the API to obtain venue information you are required to search for venues within a specified radius of a certain point, given in latitude and longitude. The challenge with Foursquare was the API rate limits which limits each search to a maximum of 49 searches. There are also daily and monthly rate limits to stay within. To obtain results of all bars, restaurants and cultural venues across Greater London with these limits an iterative algorithm had to be created which could travel across London by latitude and longitude, taking in small enough areas so as to not exceed 49 results a time. This function can be seen in figure 5.1. To achieve this, a latitude and longitude bounding box was created around London and a nested loop iteration of 50 points of latitude and 50 points of longitude was undertaken. The areas created by this had some overlap so as not to have missing areas of the capital. With a counter to check if the search limit of 49 venues was exceeded, this search algorithm put the list of venues into a pandas dataframe and de-duplicated for where areas had overlapped.

Because of the rate limits, running the algorithm for such a large area could only be done on a daily basis.

```
def importVenue(category, filename):
    df_Foursquare = pd.DataFrame()
    FrameList = []
    limit_reached = 0
    for i in range(1,50):
        for j in range(15,750,15):
            client_id = "XO1QQIQ02JE0EKQXZ4HBOYPHW2DSWJH5EIBN2AOZG2NRZVPK"
            client_secret = "GJGSIAZR4WXLYOHW4VP1JHTAMLH23EZXCWZDVPCZTYY2RQ4V"
            lat = (51.2 + (i/100.0))
            long = (-0.25 + (j/1000.0))
            if category == 'cultural':
                category_id = '4d4b7104d754a06370d81259' # cultural space
            elif category == 'restaurant':
                category_id = '4d4b7105d754a06374d81259' # food
            elif category == 'bar':
                category_id = '4d4b7105d754a06376d81259' # drink
            distance = 450
            requested_keys = ["categories","id","location","name"]
            url = "https://api.foursquare.com/v2/venues/search?ll=%s,%s&intent=browse&radius=%s&categoryId=%s&limit=49&client_id=%s&client_secret=%s&v=%s"
            % (lat, long, distance, category_id, client_id, client_secret, time.strftime("%Y%m%d"))
            resp = requests.get(url)
            dataResp = resp.json()
            if dataResp["response"]['venues'] != []:
                data = pd.DataFrame(dataResp["response"]['venues'])[requested_keys]
                df_FoursquareIteration = pd.DataFrame(data)
                if len(df_FoursquareIteration) == 49:
                    limit_reached = limit_reached + 1
                df_FoursquareIteration["categories"] = df_FoursquareIteration["categories"].apply(lambda x: dict(x[0])['name'])
                df_FoursquareIteration["lat"] = df_FoursquareIteration["location"].apply(lambda x: dict(x)["lat"])
                df_FoursquareIteration["long"] = df_FoursquareIteration["location"].apply(lambda x: dict(x)["lng"])
                FrameList.append(df_FoursquareIteration)
    df_Foursquare = pd.concat(FrameList)
    df_Foursquare.drop_duplicates(subset=['id'],keep=False)
    if limit_reached > 0:
        print('Limit Reached')
        print(limit_reached)
    columns = ['name','categories','lat','long']
    df_culture = pd.DataFrame(df_Foursquare, columns = columns)
    df_culture.to_csv(filename, index=False, encoding='utf-8')
```

FIGURE 5.1: Python function written to import data from Foursquare. This function iterates for latitude and longitude to traverse London and return venue information for one of three categories ("cultural", "food" or "nightlife) without exceeding daily API limits.

5.2 Well-being domain scores

The motivation for creating composite index scores 6 different measures of well-being was two-fold. Firstly creating a score for each index over a pre-defined scale would allow users of the front-end interactive map to compare scores across wards and give those scores some contextual meaning and significance. With 6 indices rather than the original 18 datasets, the amount of information presented to the user would not be too large to prevent a non-technical audience from interpreting the information on the map. The second reason for creating the indices was to help to try and create an interpretable model rather than one requiring significant dimension reduction. Whilst some less interpretable models will be tested to validate the quality of the quintile classification model, ideally the project and the user front end should allow us to draw some conclusions about any link between well-being and median house prices in London.

For each index three appropriate datasets were chosen and then reduced to give a single score for each ward. The 3 datasets for each index were standardised using a function in Python and those which related to a negative indicator such as emissions or crime were multiplied by a value of -1. Using this technique of standardisation gave equal weighting to each of the three indicators. Because of the equal weighting given to each indicator, these can be seen as substitutable within the context of the index which is a important factor in the choice of technique used to reduce the indicators to a score. With indicators that can be assumed to be substitutable suitable techniques would include Principal Component Analysis (PCA) and an arithmetic mean as discussed by Pareto and Adriano (Pareto, 2013). For the 6 indices, a mixture of the two techniques have been used. For those indices where the 3 indicators have some level of correlation (>0.4) the first Principal Component has been used to try and extract the largest amount of variance within the three indicators. Where the indicators for an index have low levels of correlation for at least one of the three

datasets, the arithmetic mean has been used. This approach gives us three indices which use PCA (Safety and Security, Infrastructure and Health) and three which use the mean (Education and Employment, Environment and Community Vitality and Participation).

This approach tries to maximise the information contained in all of the datasets. To create an interpretable and comparable score for each domain the resulting single scores have been normalised and then rescaled to be between 0 and 100, this is the score that is presented in the user front end.

5.3 Building a regression model

To begin the task of trying to model the median house prices from the well-being indices, a simple multiple linear regression model was used with all six indices as predictors. The results show that this model explains less than half the variance with an R squared value of 0.39. There is enough to suggest that some form of linear model may provide a reasonable model of this problem. To validate the model K-fold cross validation was used with k=7 with accuracy scores and mean squared errors averaged across the seven iterations.

The summary statistics for a simple linear model would suggest some level of statistical significance for all of the indices with Community Vitality and Participation and Education and Employment less significant than the others. Infrastructure and Health are the most significant indices here and they are also the most influential on the model. Safety and Security is the only index where there is a negative impact on house prices in the model.

TABLE 5.1: Results for regression models on London median house prices

Predictor	coef	std err	t	p
const	46.9752	135.66	0.346	0.729
Education_Employment	1.4541	0.759	1.915	0.056
Safety_Security	-4.5924	1.391	-3.301	0.001
Environment	2.0667	0.712	2.902	0.004
Vitality_Participation	2.2165	1.227	1.807	0.071
Infrastructure	9.2899	0.769	12.075	0
Health	6.2779	0.624	10.064	0

Next a polynomial model was tried with degree two. This model explained almost none of the variance with an R sq value of very close to 0. The mean squared error also increased dramatically. The polynomial model does not seem to be a strong candidate for solving the problem.

The next models involved some feature reduction based on the p values of the indices in the original linear model. This meant that first Education and Employment was removed and then Community Vitality and Participation. This resulted in a small improvement in the model fit but little improvement in the MSE.

With the median house price distribution suggesting a power law, a log transformation was performed on the data to try and linearize it with the linear regression model then re-run. This transformation dramatically increased the R squared value of the model, to 0.64, an increase of 0.25 from the equivalent model without the

transformation. The model run on the log transformed data explains an additional 25 percent of the variance within the model. The exponent of the MSE is also a substantial reduction. This returned the following model:

$$log(Median_price) = 0.00300393 * I1 + 0.00201057 * I2 + 0.00191012 * I3 + 0.0081844 * I4 + 0.01301158 * I5 + 0.00742296 * I6 \quad (5.1)$$

where I1 = Education and Employment, I2 = Safety and Security, I3 = Environment, I4 = Community Vitality and Participation, I5 = Infrastructure and I6 = Health

The equation shows that Infrastructure has the largest impact on the median house prices in the model followed by Community Vitality and Participation and then Health. All indices have a positive impact on median house prices in the model, Environment is the least influential index.

As the best performing regression model this will be used for prediction in the final visualisation.

When the predictions were given the inverse transformation and validated against the actual values, the majority of wards showed that this model had good predictive capability although there were a handful of wards where the prediction had a significant error margin. The wards with significant errors tended to be those which had a much higher or lower score in a particular domain as compared to the neighbouring areas.

TABLE 5.2: Results for regression models on London median house prices

Model	R squared	Average MSE
Linear regression	0.396	35326.75
Linear regression with polynomial degree 2	0.007	59013.81
Linear regression with 5 dimensions	0.473	33907.16
Linear regression with 4 dimensions	0.443	34608.08
Linear regression on log-transformed data	0.641	4944.06

5.4 Building the best classifier

The first model investigated was a logistic regression model. With strong interpretability a well performing logistic regression model would provide a good solution to the problem. The model had a classification success rate of 44 percent, showing a reasonable level of predictive capability across a five value classification problem. The confusion matrices provided by the seven cross-validation iterations show that model performs strongly in the first and fifth quintiles but finds it much more difficult to classify points in the second, third and fourth quintiles. From the pair-wise plots this is unsurprising as the range of median house prices is much smaller for the middle three quintiles and many of the well-being indicators are of similar magnitude.

For the second model a k-nearest neighbours classifier was used, this achieved a 40 percent classification success rate and was outperformed by the logistic regression model.

A model using a Gaussian Naive Bayes algorithm performed very slightly above the logistic regression, however, given the better interpretability of the logistic regression model, the 0.2 percent gain would not be enough to justify using this model for the solution.

The next model investigated was a decision tree, with an average classification percentage of 38, this performed significantly below the rate of the logistic regression model.

Although a single decision tree was the worst of the classifiers used so far, the next models investigated were ensemble models. A random forest was tried on the data. With 10 trees this performed below the level of the logistic regression model, but when tuned to use 100 trees, this produced the best classification score so far at just under 46 percent. The random forest was therefore a candidate to use as the classification model. Another ensemble method, gradient boosting, also performed better than the logistic regression model but was not able to match the random forest's correct classification rate.

The final model used was a Neural Network using a single hidden layer. A process of tuning this model involved trying four activation functions, of which the logistic function performed best. Different values were used for the number of nodes in the hidden layer with 45 giving the highest classification rate. By using a tuned Neural Network, a 50 percent classification rate was achieved. This was a significant improvement on the other models used.

TABLE 5.3: Results for Neural Network classifier with Logistic activation function and different numbers of nodes in the hidden layer. Based on average scores using k-fold cross validation with k=7.

Number of nodes in hidden layer	Test Score
5	0.469
10	0.477
15	0.474
20	0.490
25	0.458
30	0.471
35	0.482
40	0.451
45	0.502
50	0.488
55	0.498
60	0.496
65	0.483
70	0.501
75	0.482
80	0.480
85	0.456
90	0.490
95	0.471
100	0.490

To take advantage of both interpretability and classification success rates, it was decided to display the predicted quintile values for both the Logistic Regression

TABLE 5.4: Results for Neural Network classifier with 45 nodes in the hidden layer and different activation functions. Based on average scores using k-fold cross validation with k=7.

Activation Function	Test Score
identity	0.380
logistic	0.485
tanh	0.445
relu	0.446

model and the Neural Network in the final map visualisation. The results of testing each of the different models using k-fold cross validation with k=7 were:

TABLE 5.5: Results for classification models on the quintiles of London median house prices

Model Type	Training Score	Test Score
Logistic Regression	0.470	0.440
Decision Tree	1.000	0.388
K-Nearest Neighbours	0.614	0.407
Random Forest	1.000	0.459
Gradient Boosting	0.987	0.448
Naive Bayes	0.465	0.442

5.5 Encoding as geoJSON

To use the information from the creation of the well-being domains and the predictions obtained from the models in a JavaScript based visualisation, the information needed to be converted from a pandas dataframe in Python to a geoJSON file in JavaScript. A geoJSON file is a variation on the JSON format as defined below:

FIGURE 5.2: geoJSON specification showing Point, LineString and Polygon geometry objects.

Whilst a relatively straightforward task within the geopandas module in Python, geoJSON accepts coordinates in latitude and longitude and the shapefile being used has the coordinates defining the ward polygons in Ordnance Survey grid references. To change this to latitude and longitude required the creation of a function that would take each polygon in the ward geometry in the geo data frame and break this down into the individual points which define the polygon. Once separated into coordinate pairs, these pairs could be re-projected to be latitude and longitude. The function was then required to recombine all of the coordinate pairs into the correct polygon geometries.

```
1  def geometricTransform(gdf):
2      point_list = []
3      poly_list = []
4      for index, row in gdf.iterrows():
5          for pt in list(row['geometry'].exterior.coords):
6                inProj = Proj(init='epsg:27700') # lat long
7                outProj = Proj(init='epsg:4326') # OS National Grid
8                new_Point = transform(inProj, outProj, pt[0], pt[1])
9                point_list.append(new_Point)
10         poly = shapely.geometry.Polygon(point_list)
11         point_list = []
12         poly_list.append(poly)
13     gdf['geometry'] = gpd.GeoSeries(poly_list)
14     return(gdf)
15
16 # output geoJSON to JavaScript file defining a js variable for
       interactive map
17 def toGeoJSON(gdf):
18     json_file = gdf.to_json()
19     with open('dataset.js', 'w') as openfile:
```

```
20          openfile.write('var dataset = ' + json_file + ';')
```

The information was then in the required format to be exported to a geoJSON file.

5.6 Interactive maps

For the production of the interactive map which serves as the user front end for this project, the information was moved from the Python environment via geoJSON and into JavaScript functions embedded into html. This decision was made on the basis of the additional functionality and interactivity that could be smoothly added to the map in JavaScript. With less experience of JavaScript as a programming language, the leaflet.js tutorial (Agafonkin, 2017) was an excellent starting point.

The map has key functionality added. This includes a zoom facility and hovering over any of the 625 wards will display the median house price value and quintile, the scores for each of the six well-being domains and the predictions from both the regression and classification models.

Chapter 6

Testing and validation

6.1 Testing the data inputs

The data input software collects information from several urls where open data is published, particularly on the Greater London Authority Datastore. To ensure that the removal or changing of one of these urls does not cause the software to crash the data importer has been written as a series of functions so that each import can be run individually and unit testing can be done. This involves the use of error handling to inform the user that a specific data import has failed so that this can be isolated and investigated.

During the course of the project one link changed twice and one was removed. Because of the way the software was written, this could be easily identified and resolved. With the data importer writing information to the data store once imported, a failure in any of the import processes will not prevent the rest of the software from running if the data store has previously been populated.

For API requests, empty records are ignored and the import process will continue to run and return the populated records.

6.2 Testing the models

To test the quality and accuracy of the data models, cross-validation was employed. In each case k-fold cross-validation was the chosen method and was run with k=7 for all models. All tests on the models were run using the same starting point to ensure that the experiments were replicable.

6.3 Validating the outputs

To validate the outputs and the values showing on the map, a spot-checking technique was used. I took wards where I had an idea as to what the values should look like such as the ward in which I reside and the ward in which I work. This method alerted me to an early problem with the Education and Employment index where not all schools were being included in the import. This validation technique also confirmed that the information on the interactive map was correct. I was also able to cross-reference some of the information, for instance, Zoopla's heatmap which featured in section 2 of the report was a valuable resource to confirm that the house price choropleth maps were showing the correct values as it was relatively straightforward to compare locations between the two.

Chapter 7

Conclusions and evaluation

7.1 Lessons learnt

The project showed that well-being indicators can seem to go some way towards providing us with a model for house prices with the prediction capability and success of both the regression and classification models considerably above what would be expected from a set of unrelated data. The regression model tended to struggle more on the bottom and top quintiles whereas the classification models found the middle three quintiles more difficult to predict. The median house prices by ward definitely seem to follow a power law and the regression model was more effective when using a log transformation to make the data more linear. Infrastructure was the most influential of the well-being indices suggesting that London residents value good public transport access and short journey times to work. Wards which had a high score for infrastructure when their neighbours did not were amongst the hardest for the model to predict. With median house prices generally highest in the western central areas of London, there was less influence from the well-being scores which tended to be higher for Outer London wards. For the Environment indicator in particular, being away from the centre of London helped wards score highly due to lower pollution levels from less traffic and commerce in general. There is further potential for the link between house prices and well-being to be investigated with the use of more datasets from a greater range of sources.

The approach to the project ensured that a data-driven visualisation of the findings could be produced which was suitable for a range of users. The reduction of 18 datasets into six indices meant that the models were more interpretable than had all 18 been used to create the models. The use of geospatial analysis to analyse the data and present the results gives an excellent visual representation of what the data is showing.

I have enjoyed working on this project and would be really keen to take this work further perhaps looking at some of the extensions outlined in section 7.2. By completing the project, I have significantly improved my fluency in Python especially around the use of Pandas and Geopandas. The geospatial data elements of the project are ones that I have found particularly interesting and I hope to be able to make more use of these in the future.

7.1.1 Summary of findings

- There is some evidence of a link between well-being and house prices
- Regression models were unable to make good predictions for high-value wards with the dataset assembled

- Classification models predicted the top and bottom quintiles well but struggled more in the middle of the range
- More work is needed to produce a model of house prices based on well-being indicators that has very high levels of accuracy
- Innovative ways of data collection are required to improve the range available at ward level and at lower levels of aggregation

7.2 Possible developments

An extension of this project that would be an interesting addition to the results already displayed would be to look at whether changes in the well-being indices were related to changes in house prices. Such analysis could potentially provide insight on whether increasing house prices fuel rises in well-being indicators or whether improvements in local well-being increase demand for houses in a particular area. Correlation here would support causation, either in the case of increased demand for houses where "wellness" is high or that when house prices rise, an area will gentrify and well-being indicators will rise as a result. To achieve this, more data would need to be found that could represent all of the well-being indicators for regular intervals over a significant period of time. Given that some of the datasets are only released every few years, this may require looking at some innovative solutions of data collection with crowdsourcing and image analysis possible avenues of investigation. For instance, recent work around the analysis of social media photos has shown how cultural capital has a strong relationship with house prices an how cultural inequality can widen economic inequality as neighbourhoods become gentrified (Hristova, Aiello, and Quercia, 2018). This project has also focused on house prices, yet the rental market may also have an impact on these along with changes to how properties are used such as the increase of companies such as airbnb (Quattrone et al., 2016). Another area to look at would be how the flow of residents, particularly between neighbouring wards, can affect the house prices. For instance, if the perception of a particular area declines or potentially undesirable changes occur (e.g. large construction projects), how does the inflow and outflow affect the prices. This may be an area where the use of complex networks could assist with analysis. The other area of interest would be to go beyond the ward geographic area and use the Lower Super Output Area (LSOA) which are small census areas of around 1,500 people, grouped in such a way that the areas are seen to have similar characteristics. Whilst the full range of data used in the project is not currently available at LSOA, two of the datasets used were mapped upwards from this level and it would be a logical direction for this work to develop in. If being run as a commercial application, a paying subscription to the Foursquare and/or Google API would allow further analysis around assessing venue popularity to feed into the Community Vitality and Participation domain.

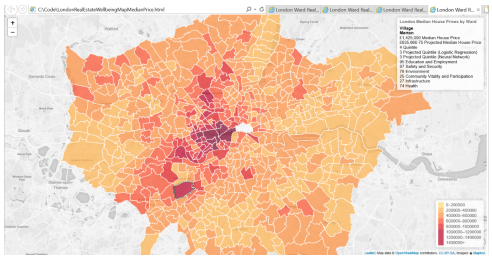
Appendix A

User manual

Please note that geoPandas and powerlaw were added to the Python environment for this project.

A fully populated data store is provided with the hard copies of the project and should be kept in the same folder as the code files.

A.1 The interactive map



There are five maps included with the project. For each map the choropleth is coloured based on a different feature.

- Median house prices
- Median house prices predicted by a linear regression model
- Quintile of median house prices
- Quintile predicted by a logistic regression model
- Quintile predicted by a neural network

To explore the map, hover over any ward to be presented with all of the well-being index scores and the predicted information. The maps also have a zoom facility to take a closer look at the data.

A.2 Python files

To run any of the data imports, choose any of the functions in the dataimporter.py file.

Please note that some imports take some time to run and those pulling data from the Foursquare API will only run once in a given data due to rate limits.

The datamodeller.py can be run at any point when the data store is populated. This will run a test on various models and write the test scores back to the data store. This has been set to export predictions based on linear regression, logistic regression and neural networks.

The MainApplication.py can be run at any time which the data store is populated. This will process the data, accept the model predictions created by the datamodeller.py file, perform the necessary geocoding and coordinate reprojections and output a JavaScript file containing the geoJSON information to feed into the map.

Appendix B

Additional tables and charts

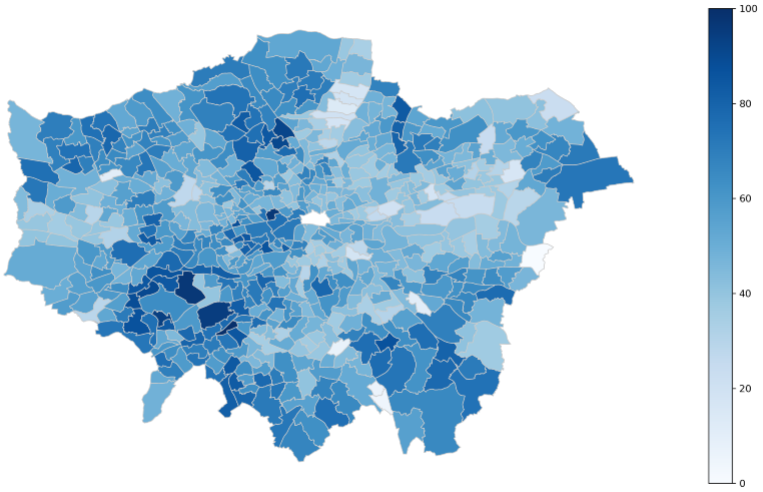


FIGURE B.1: Choropleth map showing the Education and Employment index

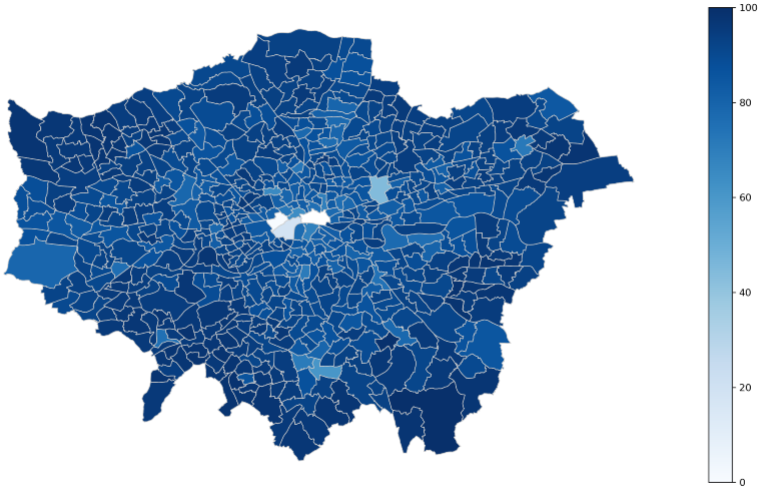


FIGURE B.2: Choropleth map showing the Safety and Security index

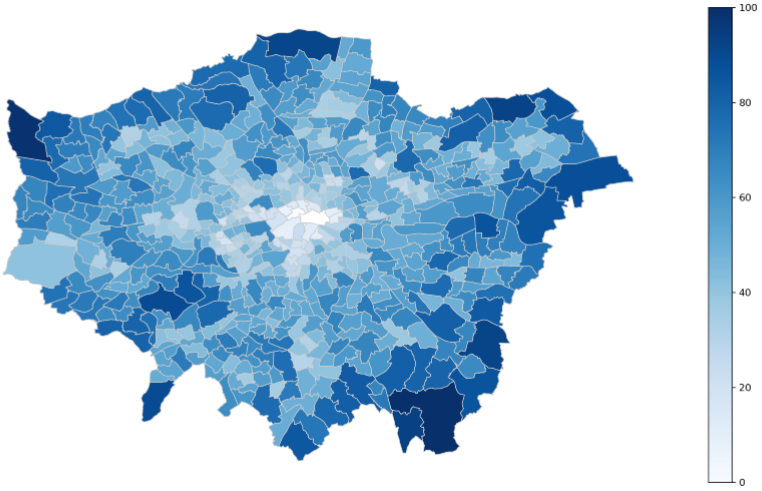


FIGURE B.3: Choropleth map showing the Environment index

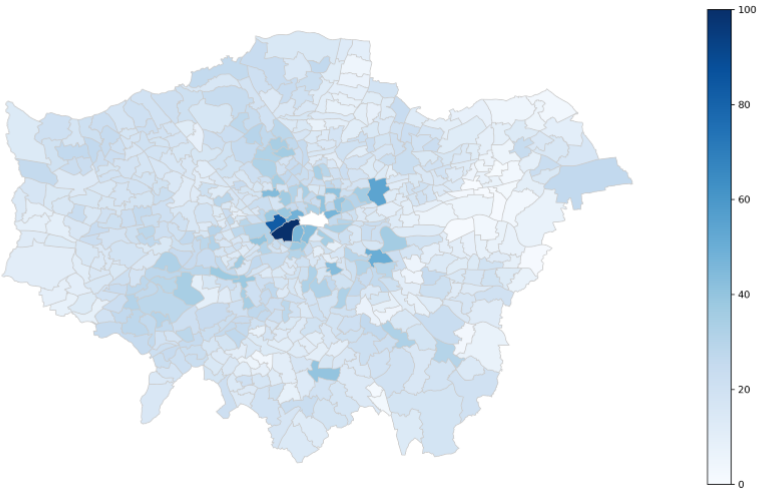


FIGURE B.4: Choropleth map showing the Community Vitality and Participation index

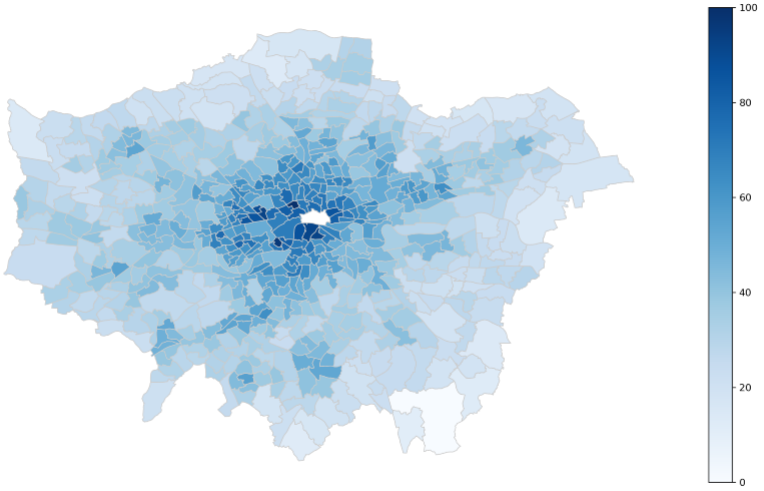


FIGURE B.5: Choropleth map showing the Infrastructure index

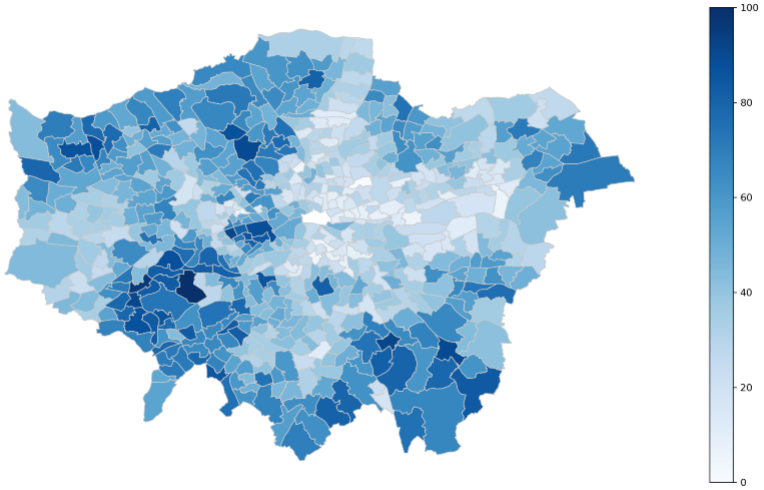


FIGURE B.6: Choropleth map showing the Health index

Appendix C

Code

Main Application

```
1
2  import pandas as pd
3  import numpy as np
4  import geopandas as gpd
5  from sklearn.preprocessing import StandardScaler, MinMaxScaler
6  from sklearn.decomposition import PCA
7  from shapely.geometry import Point, Polygon
8  from pyproj import Proj, transform
9  import shapely
10
11 def standardise(df):
12     # standardises values in a dataframe and returns new values to the
           dataframe
13     STscaler = StandardScaler()
14     scaled_values = STscaler.fit_transform(df)
15     df.loc[:,:] = scaled_values
16     return(df)
17
18 def tablestyle(df):
19     th =
           [('font-size','11px'),('text-align','centre'),('font-weight','bold')
20     ,('color','#6d6d6d'),('background-color','#f7f7f9')]
21     td = [('font-size','11px')]
22     styles = [dict(selector='th',props=th),dict(selector='td',props=td)]
23     df.style.set_table_styles(styles)
24     return(df)
25
26 # calculates domain score (out of 100) using Principal Component
       Analysis
27 # used where there is significant covariance for the three indicators
28 def domain_indicator_PCA(df, indicator_name):
29     # function runs PCA on 3 indicators in a domain and returns a score
           for domain out of 100
30     NMscaler = MinMaxScaler()
31     pca = PCA(n_components=2)
32     principalComponents = pca.fit_transform(df)
33     df['Indicator'] = pd.Series(principalComponents[:,0],index=df.index)
34     normComponents = NMscaler.fit_transform(df)
35     df_norm = df
36     df_norm.loc[:,:] = normComponents
37     indicator = df_norm.loc[:,'Indicator']*100
38     indicator.rename(columns={'Indicator':indicator_name},inplace=True)
```

```
    return(indicator)

# calculates domain score (out of 100) using arithmetic mean
# used where the three indicators have low covariance
def domain_indicator_Mean(df, indicator_name):
    df['Indicator'] = (df.iloc[:,0] + df.iloc[:,1] + df.iloc[:,2])/3
    NMscaler = MinMaxScaler()
    normComponents = NMscaler.fit_transform(df)
    df_norm = df
    df_norm.loc[:,:] = normComponents
    indicator = df_norm.loc[:,'Indicator']*100
    indicator.rename(columns={'Indicator':indicator_name},inplace=True)
    return(indicator)

# maps points to London ward polygons - projects lat long point co-ords
    to OS map grid co-ords
def mapLatLongToWard(df):
    # takes latitude and longditude of a place
    # converts co-ordinate reference system to match shapefile
    # maps point to ward polygon
    inProj = Proj(init='epsg:4326') # lat long
    outProj = Proj(init='epsg:27700') # OS National Grid
    df['points'] = df.apply(lambda row: Point(transform(inProj, outProj,
        row['long'],row['lat'])), axis=1)
    del (df['lat'], df['long'])
    df = gpd.GeoDataFrame(df, geometry='points')
    shapes = 'datastore/Shapes/London_Ward.shp'
    wards = gpd.GeoDataFrame.from_file(shapes)
    wards = wards[['GSS_CODE','geometry']]
    df = gpd.tools.sjoin(df, wards, how='left')
    df.dropna(subset=['index_right'], inplace=True)
    return(df)

# maps pre-2014 wards to best-fit post-2014 wards
# affects pre-2014 wards in Hackney, Kensington & Chelsea and Tower
    Hamlets
def old_to_new_wards(df,column_name):
    new_wards = ['E05009367','E05009368','E05009369','E05009370',
      'E05009371','E05009372','E05009373',
                'E05009374','E05009375','E05009376','E05009377',
      'E05009378','E05009379','E05009380',
                'E05009381','E05009382','E05009383','E05009384',
      'E05009385','E05009386','E05009387',
                'E05009388','E05009389','E05009390','E05009391',
      'E05009392','E05009393','E05009394',
                'E05009395','E05009396','E05009397','E05009398',
      'E05009399','E05009400','E05009401',
                'E05009402','E05009403','E05009404','E05009405',
      'E05009317','E05009318','E05009319',
                'E05009320','E05009321','E05009322','E05009323',
      'E05009324','E05009325','E05009326',
                'E05009327','E05009328','E05009332','E05009333',
      'E05009329','E05009330','E05009331',
                'E05009334','E05009335','E05009336']
    old_wards = ['E05000231','E05000232','E05000234','E05000235',
      'E05000236','E05000237','E05000238',
                'E05000249','E05000239','E05000233','E05000239',
```

```
      'E05000236','E05000241','E05000242',
                'E05000245','E05000235','E05000246','E05000243',
      'E05000247','E05000248','E05000244',
                'E05000382','E05000383','E05000384','E05000387',
      'E05000385','E05000386','E05000389',
                'E05000388','E05000389','E05000391','E05000392',
      'E05000393','E05000394','E05000395',
                'E05000396','E05000397','E05000398','E05000399',
      'E05000581','E05000575','E05000576',
                'E05000577','E05000578','E05000578','E05000583',
      'E05000583','E05000579','E05000580',
                'E05000582','E05000575','E05000586','E05000587',
      'E05000584','E05000585','E05000573',
                'E05000584','E05000588','E05000589']
    frames = []
    df_newvalues = pd.DataFrame()
    for i in range(0,len(new_wards)):
        new_frame = pd.DataFrame(df.loc[old_wards[i],:])
        new_frame.rename(columns={old_wards[i]:column_name},inplace=True)
        new_frame['ward'] = new_wards[i]
        new_frame.set_index('ward', inplace=True)
        frames.append(new_frame)
    df_newvalues = pd.concat(frames, sort=False)
    final_frames = [df, df_newvalues]
    df_newwards = pd.concat(final_frames, sort=False)
    return(df_newwards)

# function to transform ordnance survey polygon geometry to lat long
    co-ords
# required when passing to javaScript visualisation
def geometricTransform(gdf):
    point_list = []
    poly_list = []
    for index, row in gdf.iterrows():
        for pt in list(row['geometry'].exterior.coords):
             inProj = Proj(init='epsg:27700') # lat long
             outProj = Proj(init='epsg:4326') # OS National Grid
             new_Point = transform(inProj, outProj, pt[0], pt[1])
             point_list.append(new_Point)
        poly = shapely.geometry.Polygon(point_list)
        point_list = []
        poly_list.append(poly)
    gdf['geometry'] = gpd.GeoSeries(poly_list)
    return(gdf)

# output geoJSON to javascript file defining a js variable for
    interactive map
def toGeoJSON(gdf):
    json_file = gdf.to_json()
    with open('dataset.js', 'w') as openfile:
        openfile.write('var dataset = ' + json_file + ';')

# house prices
df_HousePrices = pd.read_csv('datastore/HousePrices.csv')
df_HousePrices['quintile'] = pd.qcut(df_HousePrices['Year ending Dec
    2017'],5,labels=False)
```

```
df_HousePrices['thousands'] = df_HousePrices['Year ending Dec 2017']//1000
house_price_columns = ['New code', 'Ward name', 'Borough name', 'Year ending Dec 2017', 'quintile','thousands']
df_HousePrices = pd.DataFrame(df_HousePrices, columns = house_price_columns)

# read shape file for ward polygons
shapes = 'datastore/Shapes/London_Ward.shp'
map_df = gpd.read_file(shapes)

# Domain One - Education and Employment
# employment
df_employment = pd.read_csv('datastore/Employment.csv')
df_employment.set_index('Ward_Code',inplace=True)
df_employment = df_employment.drop(['K04000001'])
df_employment = df_employment.drop(['E92000001'])
df_employment = df_employment.drop(['E12000007'])
df_employment = standardise(df_employment)
df_employment = old_to_new_wards(df_employment,'Employ_Rate')
# average GCSE scores
df_GCSE = pd.read_csv('datastore/GCSE.csv')
df_GCSE.set_index('Ward_Code',inplace=True)
df_GCSE = df_GCSE.drop(['K04000001'])
df_GCSE = df_GCSE.drop(['E92000001'])
df_GCSE = df_GCSE.drop(['E12000007'])
df_GCSE = standardise(df_GCSE)
df_GCSE = old_to_new_wards(df_GCSE,'Av_GCSE_Points')
# average Ofsted rating for schools
df_schoolslondonopen = pd.read_csv('datastore/Schools.csv')
df_schoolsborough =
df_schoolslondonopen.pivot_table(values='Ofsted_Rating', index='DistrictAdministrative (code)', fill_value=0)
df_schools =
df_schoolslondonopen.pivot_table(values='Ofsted_Rating', index='AdministrativeWard (code)', fill_value=0)
df_schoolward = pd.merge(map_df, df_schools, left_on='GSS_CODE', right_index=True, how='outer')
df_schools =
pd.merge(df_schoolward,df_schoolsborough, left_on='LB_GSS_CD', right_index=True, how='outer')
df_schools['Ofsted_Rating_x'].fillna(df_schools['Ofsted_Rating_y'], inplace=True)
final_columns = ['GSS_CODE','Ofsted_Rating_x']
df_schools = pd.DataFrame(df_schools, columns = final_columns)
df_schools.set_index('GSS_CODE',inplace=True)
df_schools = standardise(df_schools)
# merge the 3 indicators to create the domain
df_edu = pd.merge(df_GCSE,df_schools, left_index=True, right_index=True)
df_eduemploy = pd.merge(df_employment,df_edu, left_index=True, right_index=True)
# check covariance and correlation matrices
df_eduemploy_cov = df_eduemploy.cov()
df_eduemploy_corr = df_eduemploy.corr()
df_eduemploy_corr.to_csv('datastore/eduemploycorr.csv')
## run principal component analysis to create domain score
```

```
193 Education_Employment =
        domain_indicator_Mean(df_eduemploy,'Education_Employment')
194
195 # Domain Two - Safety and Security
196 # crime (against the person and locality crime)
197 df_crime = pd.read_csv('datastore/Crime.csv')
198 df_crime_pivot = df_crime.pivot_table(index='WardCode', columns='Major
        Category', values='2017',aggfunc='sum')
199 person_columns = ['Robbery','Sexual Offences','Violence Against the
        Person']
200 area_columns = ['Burglary','Criminal Damage','Drugs','Theft and
        Handling']
201 df_crimeperson = pd.DataFrame(df_crime_pivot, columns = person_columns)
202 df_crimeperson = standardise(df_crimeperson)
203 df_crimearea = pd.DataFrame(df_crime_pivot, columns = area_columns)
204 df_crimearea = standardise(df_crimearea)
205 # traffic danger
206 df_traffic = pd.read_csv('datastore/Traffic.csv')
207 df_traffic.set_index('Ward_Code',inplace=True)
208 df_traffic = standardise(df_traffic)
209 df_traffic['traffic_fatality_score'] = (df_traffic['Fatal'] +
        df_traffic['Serious'] + df_traffic['Slight'])/3
210 del df_traffic['Fatal']
211 del df_traffic['Serious']
212 del df_traffic['Slight']
213 # merge the 3 indicators to create the domain
214 df_crime = pd.merge(df_crimeperson, df_crimearea, left_index=True,
        right_index=True)
215 df_safetysecurity = pd.merge(df_crime,df_traffic, left_index=True,
        right_index=True)
216 # check covariance and correlation matrices
217 df_safetysecurity_cov = df_safetysecurity.cov()
218 df_safetysecurity_corr = df_safetysecurity.corr()
219 df_safetysecurity_corr.to_csv('datastore/safetysecuritycorr.csv')
220 # run principal component analysis to create domain score
221 Safety_Security =
        100-domain_indicator_PCA(df_safetysecurity,'Safety_Security')
222
223 # Domain Three - Environment
224 # emissions
225 df_emissions = pd.read_csv('datastore/Emissions.csv')
226 df_emissions.set_index('Ward_Code',inplace=True)
227 df_emissions = df_emissions.drop(['K04000001'])
228 df_emissions = df_emissions.drop(['E92000001'])
229 df_emissions = df_emissions.drop(['E12000007'])
230 df_emissions = standardise(df_emissions)
231 df_emissions['emission'] = (df_emissions['PM10'] +
        df_emissions['NO2'])/2
232 df_emissions = pd.DataFrame(df_emissions['emission']*-1) # emissions
        negative so *-1
233 df_emissions = old_to_new_wards(df_emissions,'emission')
234 # greenspace
235 df_greenspace = pd.read_csv('datastore/Greenspace.csv')
236 df_greenspace.set_index('Ward_Code',inplace=True)
237 df_greenspace = df_greenspace.drop(['K04000001'])
238 df_greenspace = df_greenspace.drop(['E92000001'])
239 df_greenspace = df_greenspace.drop(['E12000007'])
```

```
df_greenspace = standardise(df_greenspace)
df_greenspace = old_to_new_wards(df_greenspace,'Greenspace%')
# nature
df_nature = pd.read_csv('datastore/Nature.csv')
df_nature.set_index('Ward_Code',inplace=True)
df_nature = standardise(df_nature)
df_nature = old_to_new_wards(df_nature,'Nature_Access')
# merge the 3 indicators to create the domain
df_green = pd.merge(df_nature,df_greenspace, left_index=True,
    right_index=True)
df_environment = pd.merge(df_green,df_emissions, left_index=True,
    right_index=True)
# check covariance and correlation matrices
df_environment_cov = df_environment.cov()
df_environment_corr = df_environment.corr()
df_environment_corr.to_csv('datastore/environmentcorr.csv')
# create domain indicator using arithmetic mean
Environment = domain_indicator_Mean(df_environment,'Environment')

# Domain Four - Community Vitality and Participation
# election turnout
df_turnout = pd.read_csv('datastore/ElectionTurnout.csv')
df_turnout.set_index('Ward_Code', inplace=True)
df_turnout = standardise(df_turnout)
# access to cultural spaces
cultural_venues = pd.read_csv('datastore/CulturalVenues.csv')
cultural_locations = mapLatLongToWard(cultural_venues)
df_culturepivot =
cultural_locations.pivot_table(index='GSS_CODE',
    values='name',aggfunc='count')
df_cultureaccess = standardise(df_culturepivot)
# access to food and drink establishment
bars = pd.read_csv('datastore/Bars.csv')
restaurants = pd.read_csv('datastore/Restaurants.csv')
food_drink_list = [bars, restaurants]
bars_restaurants = pd.concat(food_drink_list)
# specify co-ordinate reference systems
bar_restaurant_locations = mapLatLongToWard(bars_restaurants)
df_barrestaurantpivot =
bar_restaurant_locations.pivot_table(index='GSS_CODE',
    values='name',aggfunc='count')
df_barrestaurant = standardise(df_barrestaurantpivot)
df_barrestaurant.rename(columns={'name':'name_y'},inplace=True)
# merge the 3 indicators to create the domain
df_participation = df_turnout.join(df_cultureaccess, how='outer')
df_vitalityparticipation = df_participation.join(df_barrestaurant,
    how='outer')
df_vitalityparticipation['name'].fillna(0.0, inplace=True)
df_vitalityparticipation['name_y'].fillna(0.0, inplace=True)
df_vitalityparticipation['Turnout'].fillna(0.0, inplace=True)
# check covariance and correlation matrices
df_vitalityparticipation_cov = df_vitalityparticipation.cov()
df_vitalityparticipation_corr = df_vitalityparticipation.corr()
df_vitalityparticipation_corr.to_csv('datastore/vitalityparticipationcorr.csv')
# create domain indicator using arithmetic mean
Vitality_Participation =
    domain_indicator_Mean(df_vitalityparticipation,'Vitality_Participation')
```

```
291
292 # Domain Five - Infrastructure
293 # access to public transportation
294 df_pta = pd.read_csv('datastore/TransportAccess.csv')
295 df_pta.set_index('Ward Code',inplace=True)
296 df_pta = standardise(df_pta)
297 # average journey times
298 df_journeys = pd.read_csv('datastore/JourneyTimes.csv')
299 df_journeypivot = df_journeys.pivot_table(index='GSS_CODE',
        values='JourneyTime')
300 df_journeys = standardise(df_journeypivot)*-1
301 # population density
302 df_density = pd.read_csv('datastore/PopDensity.csv')
303 df_density.set_index('Code',inplace=True)
304 df_density = standardise(df_density)*-1
305 df_density =
        old_to_new_wards(df_density,'Population_per_square_kilometre')
306 # merge the 3 indicators to create the domain
307 df_transportation = pd.merge(df_pta,df_journeys, left_index=True,
        right_index=True)
308 df_infrastructure = pd.merge(df_transportation,df_density,
        left_index=True, right_index=True)
309 # check covariance and correlation matrices
310 df_infrastructure_cov = df_infrastructure.cov()
311 df_infrastructure_corr = df_infrastructure.corr()
312 df_infrastructure_corr.to_csv('datastore/infrastructurecorr.csv')
313 # create domain indicator using PCA
314 Infrastructure =
        domain_indicator_PCA(df_infrastructure,'Infrastructure')
315
316 # Domain Six - Health
317 # life expectancy
318 df_expectancy = pd.read_csv('datastore/LifeExpectancy.csv')
319 df_expectancy.set_index('Ward_Code', inplace=True)
320 df_expectancy = standardise(df_expectancy)
321 df_expectancy = old_to_new_wards(df_expectancy,'Life_Ex')
322 # childhood obesity
323 df_obesity = pd.read_csv('datastore/ChildObesity.csv')
324 df_obesity.set_index('Code_x', inplace=True)
325 df_obesity = standardise(df_obesity)*-1
326 # illness affecting work
327 df_illness = pd.read_csv('datastore/Illness.csv')
328 df_illnesspivot
329 = df_illness.pivot_table(index='GSS_CODE',values='Comparative illness
        and disability ratio indicator')
330 df_illness = standardise(df_illnesspivot)*-1
331 # merge the 3 indicators to create the domain
332 df_prehealth = pd.merge(df_illness,df_obesity, left_index=True,
        right_index=True)
333 df_health = pd.merge(df_prehealth,df_expectancy, left_index=True,
        right_index=True)
334 # check covariance and correlation matrices
335 df_health_cov = df_health.cov()
336 df_health_corr = df_health.corr()
337 df_health_corr.to_csv('datastore/healthcorr.csv')
338 # build domain indicator using PCA
339 Health = domain_indicator_PCA(df_health,'Health')
```

```
340
341 # build data set for modelling
342 DataSet =
343 pd.merge(df_HousePrices, pd.DataFrame(Education_Employment), left_on =
        'New code', right_index = True)
344 DataSet.rename(columns={0:'Education_Employment'},inplace=True)
345 DataSet = pd.merge(DataSet, pd.DataFrame(Safety_Security), left_on =
        'New code', right_index = True)
346 DataSet.rename(columns={0:'Safety_Security'},inplace=True)
347 DataSet = pd.merge(DataSet, pd.DataFrame(Environment), left_on = 'New
        code', right_index = True)
348 DataSet.rename(columns={0:'Environment'},inplace=True)
349 DataSet = pd.merge(DataSet, pd.DataFrame(Vitality_Participation),
        left_on = 'New code', right_index = True)
350 DataSet.rename(columns={0:'Vitality_Participation'},inplace=True)
351 DataSet = pd.merge(DataSet, pd.DataFrame(Infrastructure), left_on =
        'New code', right_index = True)
352 DataSet.rename(columns={0:'Infrastructure'},inplace=True)
353 DataSet = pd.merge(DataSet, pd.DataFrame(Health), left_on = 'New code',
        right_index = True)
354 DataSet.rename(columns={0:'Health','Year ending Dec
        2017':'Median_Price'},inplace=True)
355 DataSet.to_csv('datastore/DataSet.csv', index=False)
356
357 df_predictions = pd.read_csv('datastore/predictions.csv')
358
359 df_datasetmapping =
360 gpd.GeoDataFrame(pd.merge(map_df, df_predictions, left_on='GSS_CODE',
        right_on='New code'))
361
362 df_datasetmapping.to_csv('datastore/datasetmapping.csv')
363
364 df_js = geometricTransform(df_datasetmapping)
365
366 toGeoJSON(df_js)
```

Data Modeller

```
1
2 import pandas as pd
3 import numpy as np
4 from sklearn import linear_model
5 from sklearn.preprocessing import PolynomialFeatures
6 from sklearn.model_selection import KFold
7 from sklearn.metrics import mean_squared_error
8 import statsmodels.api as sm
9 import seaborn as sns
10 import powerlaw
11 from sklearn.linear_model import LogisticRegression
12 from sklearn.neural_network import MLPClassifier
13 from sklearn.model_selection import KFold
14 from sklearn.tree import DecisionTreeClassifier
15 from sklearn.neighbors import KNeighborsClassifier
16 from sklearn.ensemble import GradientBoostingClassifier
17 from sklearn.ensemble import RandomForestClassifier
18 from sklearn.naive_bayes import GaussianNB
19 import math
```

```
from sklearn.metrics import classification_report,
confusion_matrix, mean_squared_error, accuracy_score


np.random.seed(100)

# create datasets and specify validation model
dataset = pd.read_csv('files/DataSet.csv')
validation = KFold(n_splits=7, shuffle=True, random_state=None)

columns = ['Education_Employment', 'Safety_Security', 'Environment',
    'Vitality_Participation',
              'Infrastructure', 'Health', 'thousands']
DataVars = pd.DataFrame(dataset, columns=columns)
y = np.ravel(pd.DataFrame(dataset['thousands']))
X = DataVars
del X['thousands']

pl_fit = powerlaw.Fit(y)

pl_alpha = pl_fit.power_law.alpha
pl_sigma = pl_fit.power_law.sigma


# use statsmodel for model summary
X_sm = sm.add_constant(X)
stats_model = sm.OLS(y, X_sm)
stats_model_estimate = stats_model.fit()
print(stats_model_estimate.summary())


# linear regression
linearr_score = 0
linearr_error = 0

for train_index, test_index in validation.split(X):
    X_train, X_test = np.array(X)[train_index], np.array(X)[test_index]
    y_train, y_test = np.array(y)[train_index], np.array(y)[test_index]
    lm = linear_model.LinearRegression()
    model = lm.fit(X_train, y_train)
    predictions = lm.predict(X_test)
    linearr_score = linearr_score + model.score(X_test, y_test)
    linearr_error = linearr_error + mean_squared_error(y_test,
        predictions)
linearr_score = linearr_score/7
linearr_error = linearr_error/7

lr_list = pd.DataFrame([['Linear Regression', linearr_score,
    linearr_error]])

linearr_score = 0
linearr_error = 0

poly2 = PolynomialFeatures(degree=2)
X2 = poly2.fit_transform(X)
for train_index, test_index in validation.split(X2):
```

```
    X2_train, X2_test = np.array(X2)[train_index],
        np.array(X2)[test_index]
    y_train, y_test = np.array(y)[train_index], np.array(y)[test_index]
    clm = linear_model.LinearRegression()
    model = clm.fit(X2_train, y_train)
    predictions = clm.predict(X2_test)
    linearr_score = linearr_score + model.score(X2_test, y_test)
    linearr_error = linearr_error + mean_squared_error(y_test,
        predictions)
linearr_score = linearr_score/7
linearr_error = linearr_error/7

lr_list_poly2 = pd.DataFrame([['Linear Regression (poly 2)',
    linearr_score, linearr_error]])

# reduce features
del X['Vitality_Participation']
linearr_score = 0
linearr_error = 0

for train_index, test_index in validation.split(X):
    X_train, X_test = np.array(X)[train_index], np.array(X)[test_index]
    y_train, y_test = np.array(y)[train_index], np.array(y)[test_index]
    lm = linear_model.LinearRegression()
    model = lm.fit(X_train, y_train)
    predictions = lm.predict(X_test)
    linearr_score = linearr_score + model.score(X_test, y_test)
    linearr_error = linearr_error + mean_squared_error(y_test,
        predictions)
linearr_score = linearr_score/7
linearr_error = linearr_error/7

lr_list_5dim = pd.DataFrame([['Linear Regression (reduced to 5 dim)',
    linearr_score, linearr_error]])

del X['Education_Employment']
linearr_score = 0
linearr_error = 0

for train_index, test_index in validation.split(X):
    X_train, X_test = np.array(X)[train_index], np.array(X)[test_index]
    y_train, y_test = np.array(y)[train_index], np.array(y)[test_index]
    lm = linear_model.LinearRegression()
    model = lm.fit(X_train, y_train)
    predictions = lm.predict(X_test)
    linearr_score = linearr_score + model.score(X_test, y_test)
    linearr_error = linearr_error + mean_squared_error(y_test,
        predictions)
linearr_score = linearr_score/7
linearr_error = linearr_error/7

lr_list_4dim = pd.DataFrame([['Linear Regression (reduced to 4 dim)',
    linearr_score, linearr_error]])

# try a log transformation of the data
dataset = pd.read_csv('files/DataSet.csv')
validation = KFold(n_splits=7, shuffle=True, random_state=None)
```

```
123
124 columns = ['Education_Employment', 'Safety_Security', 'Environment',
        'Vitality_Participation',
125                 'Infrastructure', 'Health', 'Median_Price']
126 DataVars = pd.DataFrame(dataset, columns=columns)
127 y = np.log(np.ravel(pd.DataFrame(dataset['Median_Price'])))
128 X = DataVars
129 #X.apply(np.log)
130 #X.replace(np.nan,0)
131 del X['Median_Price']
132
133 for train_index, test_index in validation.split(X):
134     X_train, X_test = np.array(X)[train_index], np.array(X)[test_index]
135     y_train, y_test = np.array(y)[train_index], np.array(y)[test_index]
136     lm = linear_model.LinearRegression()
137     model = lm.fit(X_train, y_train)
138     predictions = lm.predict(X_test)
139     linearr_score = linearr_score + model.score(X_test, y_test)
140     linearr_error = linearr_error + mean_squared_error(y_test,
            predictions)
141 linearr_score = linearr_score/7
142 linearr_error = linearr_error/7
143
144 lr_list_logtrans = pd.DataFrame([['Linear Regression (Log Transform)',
        linearr_score, linearr_error]])
145
146 model_results = pd.concat([lr_list, lr_list_poly2, lr_list_5dim,
        lr_list_4dim, lr_list_logtrans])
147 model_results.rename(columns={0:'Model Type',1:'Av. R sq',2:'Av.
        MSE'},inplace=True)
148
149 print(model.coef_, model.intercept_)
150
151 new_data = pd.DataFrame(dataset)
152 new_data['predicted'] = np.exp(pd.Series(lm.predict(X)))
153
154 model_results.to_csv('files/regression.csv', index=False)
155
156 np.random.seed(100)
157 # create datasets and specify validation model
158 dataset = pd.read_csv('files/DataSet.csv')
159 validation = KFold(n_splits=7, shuffle=True, random_state=None)
160
161 columns = ['Education_Employment', 'Safety_Security', 'Environment',
        'Vitality_Participation',
162                 'Infrastructure', 'Health', 'quintile']
163
164 DataVars = pd.DataFrame(dataset, columns=columns)
165 y = np.ravel(pd.DataFrame(dataset['quintile']))
166 X = DataVars
167 del X['quintile']
168
169 classification_models = [LogisticRegression(),
        DecisionTreeClassifier(), KNeighborsClassifier(),
170                         RandomForestClassifier(n_estimators=100),
                                GradientBoostingClassifier(), GaussianNB()]
```

```
classification_model_labels = ['Logistic Regression', 'Decision Tree', 'K-Nearest Neighbours',
                               'Random Forest', 'Gradient Boosting', 'Naive Bayes']

result_list = []
# classification models
for i in range(0,len(classification_models)):
    np.random.seed(100)
    classification_score = 0
    training_score = 0
    prediction_score = 0
    for train_index, test_index in validation.split(X):
        X_train, X_test = np.array(X)[train_index], np.array(X)[test_index]
        y_train, y_test = np.array(y)[train_index], np.array(y)[test_index]
        classifier = classification_models[i]
        model = classifier.fit(X_train, y_train)
        predictions = model.predict(X_test)
        for j in range(0,len(y_test)):
            prediction_score = prediction_score + ((model.predict(X_test)[j]-y_test[j])*(model.predict(X_test)[j]-y_test[j]))
        training_score = training_score + accuracy_score(y_train, model.predict(X_train))
        classification_score = classification_score + accuracy_score(y_test, predictions)
    result = [classification_model_labels[i], training_score/7, classification_score/7, math.sqrt(prediction_score/7)]
    result_list.append(result)
result_df = pd.DataFrame(result_list)
result_df.rename(columns={0:'Model Type',1:'Training Score',2:'Test Score',3:'Prediction Error'}, inplace=True)
result_df.to_csv('files/classificationResults.csv', index=False)

# tune Neural Network for hidden layer
np.random.seed(100)
neural_size_results = []
for i in range(1,21):
    classification_score = 0
    for train_index, test_index in validation.split(X):
        X_train, X_test = np.array(X)[train_index], np.array(X)[test_index]
        y_train, y_test = np.array(y)[train_index], np.array(y)[test_index]
        nn = MLPClassifier(hidden_layer_sizes=(i*5),activation='logistic',max_iter=1000)
        network = nn.fit(X_train, y_train)
        predictions = nn.predict(X_test)
        classification_score = classification_score + accuracy_score(y_test, predictions)
    neural_size = [i*5,classification_score/7]
    neural_size_results.append(neural_size)
neuralsize_df = pd.DataFrame(neural_size_results)
```

```
neuralsize_df.rename(columns={0:'Nodes in hidden layer',1:'Test Score'}, inplace=True)
neuralsize_df.to_csv('files/neuralsizeResults.csv', index=False)

# tune Neural Network for best activation function
np.random.seed(100)
activation_functions = ['identity','logistic','tanh','relu']
neural_act_results = []
for j in range(0,len(activation_functions)):
    classification_score = 0
    for train_index, test_index in validation.split(X):
        X_train, X_test = np.array(X)[train_index], np.array(X)[test_index]
        y_train, y_test = np.array(y)[train_index], np.array(y)[test_index]
        nn = MLPClassifier(hidden_layer_sizes=(45),activation=activation_functions[j],max_iter=1000)
        network = nn.fit(X_train, y_train)
        predictions = nn.predict(X_test)
        classification_score = classification_score + accuracy_score(y_test, predictions)
    neural_act = [activation_functions[j],classification_score/7]
    neural_act_results.append(neural_act)
neuralact_df = pd.DataFrame(neural_act_results)
neuralact_df.rename(columns={0:'Activation Function',1:'Test Score'}, inplace=True)
neuralact_df.to_csv('files/neuralactivationResults.csv', index=False)

chosen_classifier = LogisticRegression()
chosen_model = chosen_classifier.fit(X, y)
chosen_predictions = chosen_model.predict(X)
new_data['Logistic'] = pd.Series(chosen_predictions)

neural_classifier = MLPClassifier(hidden_layer_sizes=(45),activation='logistic',max_iter=1000)
neural_model = neural_classifier.fit(X, y)
nn_predictions = neural_model.predict(X)
new_data['NeuralNetwork'] = pd.Series(nn_predictions)

new_data.to_csv('files/predictions.csv')
```

Data Importer

```

import pandas as pd
import numpy as np
import time
import requests
import geopandas as gpd

def importHousePrices():
    XLS_HOUSE_PRICE = 'https://data.london.gov.uk/download/average-house-prices/fb8116f5-06f8-42e0-aa6c-b0b1bd69cdba/land-registry-house-prices-ward.xls'
    try:
```

```
14          df_HousePricesAll =
                pd.read_excel(XLS_HOUSE_PRICE,'Median',skiprows=[1])
15      except:
16          print('Cannot open data file - London House Prices')
17      df_HousePrices = pd.DataFrame(df_HousePricesAll.iloc[1:,:])
18      df_HousePrices.to_csv('datastore/HousePrices.csv',index=False)
19      return(df_HousePrices)
20
21  def importEmploymentRates():
22      XLSX_WARD_ATLAS =
23    'https://files.datapress.com/london/dataset/ward-profiles-and-atlas
24    /2015-09-24T14:48:35/ward-atlas-data.xls'
25      try:
26          df_ward_atlas2 = pd.read_excel(XLSX_WARD_ATLAS, 'iadatasheet2',
                skiprows=2)
27      except:
28          print('Cannot open data file - Ward Atlas Sheet 2')
29      employment_columns = ['New Code','Economically active: % In
            employment.1']
30      df_employment = pd.DataFrame(df_ward_atlas2, columns =
            employment_columns)
31      df_employment.rename(columns=
32    {'New Code':'Ward_Code','Economically active: % In
          employment.1':'Employ_Rate'},inplace=True)
33      df_employment.to_csv('datastore/Employment.csv',index=False)
34      return(df_employment)
35
36  def importGCSE():
37      XLSX_WARD_ATLAS =
38    'https://files.datapress.com/london/dataset/ward-profiles-and-atlas
39    /2015-09-24T14:48:35/ward-atlas-data.xls'
40      try:
41          df_ward_atlas3 = pd.read_excel(XLSX_WARD_ATLAS, 'iadatasheet3',
                skiprows=2)
42      except:
43          print('Cannot open data file - Ward Atlas Sheet 3')
44      GCSE_columns = ['New Code','2014.2']
45      df_GCSE = pd.DataFrame(df_ward_atlas3, columns = GCSE_columns)
46      df_GCSE.rename(columns={'New
            Code':'Ward_Code','2014.2':'Av_GCSE_Points'},inplace=True)
47      df_GCSE.to_csv('datastore/GCSE.csv',index=False)
48      return(df_GCSE)
49
50  def importSchools():
51      # from https://get-information-schools.service.gov.uk/Downloads
52      CSV_SCHOOLS =
53     'http://ea-edubase-api-prod.azurewebsites.net/edubase/edubasealldata20180908.csv'
54      try:
55          iter_csv = pd.read_csv(CSV_SCHOOLS, iterator=True,
                chunksize=1000)
56          df_schoolsall = pd.DataFrame()
57          df_schoolsall = pd.concat([chunk[chunk['GOR (name)'] ==
                'London'] for chunk in iter_csv])
58      except:
59          print('Cannot open data file - SchoolsData')
60      df_schoolslondonopen =
            df_schoolsall[(df_schoolsall['EstablishmentStatus (code)'] == 1)]
```

```
61      df_schoolslondonopen['OfstedRating (name)'].replace('', np.nan,
            inplace=True)
62      df_schoolslondonopen.dropna(subset=['OfstedRating (name)'],
            inplace=True)
63      df_schoolslondon = pd.DataFrame(df_schoolslondonopen)
64      df_schoolslondon.rename(columns={'OfstedRating
            (name)':'Ofsted_Rating'}, inplace=True)
65      ofsted_ratings =
66    {'Ofsted_Rating':{'Outstanding':2,'Good':1,'Requires improvement':-1,
67    'Serious Weaknesses':-2,'Special Measures':-2,'Inadequate':-2}}
68      df_schoolslondon.replace(ofsted_ratings,inplace=True)
69      df_schoolslondon.to_csv('datastore/Schools.csv',index=False)
70      return(df_schoolslondon)
71
72  def importCrime():
73      CSV_CRIME =
74    'https://data.london.gov.uk/download/recorded_crime_summary
75    /866c05de-c5cd-454b-8fe5-9e7c77ea2313/
76    MPS%20Ward%20Level%20Crime%20%28most%20recent%2024%20months%29.csv'
77      try:
78          df_crime = pd.read_csv(CSV_CRIME)
79      except:
80          print('Cannot open data file - Crime by Ward')
81      df_crime['2017'] = df_crime['201701']+df_crime['201702']
82    +df_crime['201703']+df_crime['201704']+
83    df_crime['201705']+df_crime['201706']+df_crime['201707']
84    +df_crime['201708']+df_crime['201709']
85    +df_crime['201710']+df_crime['201711']+df_crime['201712']
86      df_crime.to_csv('datastore/Crime.csv', index=False)
87      return(df_crime)
88
89  def importTraffic():
90      XLSX_TRAFFIC_FATALITIES =
91    'https://files.datapress.com/london/dataset/
92    road-casualties-severity-borough/road-casualties-severity-lsoa-msoa-ward.xls'
93      try:
94          df_traffic_f = pd.read_excel(XLSX_TRAFFIC_FATALITIES, 'Ward 2014
                only', skiprows=1)
95          df_traffic_f2 = pd.read_excel(XLSX_TRAFFIC_FATALITIES,
                'Ward(pre2014)', skiprows=1)
96      except:
97          print('Cannot open data file - Traffic Fatalities by Ward')
98      traffic_columns = ['Unnamed: 0','1 Fatal.9','2 Serious.9','3
            Slight.9']
99      traffic_columns2 = ['Ward Code','Fatal.4','Serious.4','Slight.4']
100     df_traffic_fatalities = pd.DataFrame(df_traffic_f, columns =
            traffic_columns)
101     df_traffic_fatalities2 = pd.DataFrame(df_traffic_f2, columns =
            traffic_columns2)
102     df_traffic_fatalities.rename(columns=
103   {'Unnamed: 0':'Ward_Code','1 Fatal.9':'Fatal','2
        Serious.9':'Serious','3 Slight.9':'Slight'},
104    inplace=True)
105     df_traffic_fatalities2.rename(columns={'Ward
            Code':'Ward_Code','Fatal.4':'Fatal','Serious.4':'Serious','Slight.4':'Slight'},
106   inplace=True)
```

```
107     df_traffic_fatalities = pd.concat([df_traffic_fatalities,
            df_traffic_fatalities2])
108     df_traffic_fatalities.to_csv('datastore\Traffic.csv', index=False)
109
110 def importEmissions():
111     XLSX_WARD_ATLAS =
112   'https://files.datapress.com/london/dataset/ward-profiles-and-atlas
113   /2015-09-24T14:48:35/ward-atlas-data.xls'
114     try:
115         df_ward_atlas5 = pd.read_excel(XLSX_WARD_ATLAS, 'iadatasheet5',
              skiprows=2)
116     except:
117         print('Cannot open data file - Ward Atlas Sheet 5')
118     emissions_columns = ['New Code','2011.4','2011.6']
119     df_emissions = pd.DataFrame(df_ward_atlas5, columns =
            emissions_columns)
120     df_emissions.rename(columns={'New
            Code':'Ward_Code','2011.4':'PM10','2011.6':'NO2'},inplace=True)
121     df_emissions.to_csv('datastore/Emissions.csv', index=False)
122     return(df_emissions)
123
124 def importGreenspace():
125     XLSX_WARD_ATLAS =
126   'https://files.datapress.com/london/dataset/ward-profiles-and-atlas
127   /2015-09-24T14:48:35/ward-atlas-data.xls'
128     try:
129         df_ward_atlas5 = pd.read_excel(XLSX_WARD_ATLAS, 'iadatasheet5',
              skiprows=2)
130     except:
131         print('Cannot open data file - Ward Atlas Sheet 5')
132     greenspace_columns = ['New Code','2014.4']
133     df_greenspace = pd.DataFrame(df_ward_atlas5, columns =
            greenspace_columns)
134     df_greenspace.rename(columns={'New
            Code':'Ward_Code','2014.4':'Greenspace%'},inplace=True)
135     df_greenspace.to_csv('datastore/Greenspace.csv', index=False)
136
137 def importNature():
138     CSV_NATURE_ACCESS =
139   'https://files.datapress.com/london/dataset/access-public-open-space-and-nature-ward/
140   public-open-space-nature-ward_access-to-nature.csv'
141     try:
142         df_nature_access = pd.read_csv(CSV_NATURE_ACCESS)
143     except:
144         print('Cannot open data file - Nature Access by Ward')
145     nature_columns = ['Ward','% homes with good access to nature']
146     df_nature = pd.DataFrame(df_nature_access, columns = nature_columns)
147     df_nature.rename(columns=
148   {'Ward':'Ward_Code', '% homes with good access to
        nature':'Nature_Access'},inplace=True)
149     df_nature.to_csv('datastore/Nature.csv', index=False)
150
151 def importElection():
152     XLSX_ELECTION =
153   'https://files.datapress.com/london/dataset/london-elections-results-2016-wards-boroughs
154     /2016-05-27T10:46:12/gla-elections-votes-all-2016.xlsx'
155     try:
```

```
156         df_election = pd.read_excel(XLSX_ELECTION, 'Wards & Postals',
                skiprows=2)
157     except:
158         print('Cannot open data file - Election Turnout by Ward')
159     df_turnout = df_election[(df_election['Unnamed: 2'] == 'Ward')]
160     turnout_columns = ['Unnamed: 4','% Turnout']
161     df_turnout = pd.DataFrame(df_turnout, columns = turnout_columns)
162     df_turnout.rename(columns={'Unnamed: 4':'Ward_Code', '%
            Turnout':'Turnout'},inplace=True)
163     df_turnout.to_csv('datastore/ElectionTurnout.csv', index=False)
164     return(df_turnout)
165
166 def importVenue(category, filename):
167     df_Foursquare = pd.DataFrame()
168     FrameList = []
169     limit_reached = 0
170     for i in range(1,50):
171         for j in range(15,750,15):
172             client_id = "XO1QQIQO2JEOEKQXZ4HBOYPHW2DSWJH5EIBN2AOZG2NRZVPK"
173             client_secret =
                    "GJGSIAZR4WXLYOHW4VP1JHTAMLH23EZXCWZDVPCZTYY2RQ4V"
174             lat = (51.2 + (i/100.0))
175             long = (-0.25 + (j/1000.0))
176             if category == 'cultural':
177                 category_id = '4d4b7104d754a06370d81259' # cultural space
178             elif category == 'restaurant':
179                 category_id = '4d4b7105d754a06374d81259' # food
180             elif category == 'bar':
181                 category_id = '4d4b7105d754a06376d81259' # drink
182             distance = 450
183             requested_keys = ["categories","id","location","name"]
184             url = "https://api.foursquare.com/v2/venues/search?ll=
185     %s,%s&intent=browse&radius=%s&categoryId=%s&limit=49&client_id=%s&client_secret=%s&v=
186     %s"% (lat, long, distance, category_id, client_id, client_secret,
            time.strftime("%Y%m%d"))
187             resp = requests.get(url)
188             dataResp = resp.json()
189             if dataResp["response"]['venues'] != []:
190                 data =
                        pd.DataFrame(dataResp["response"]['venues'])[requested_keys]
191                 df_FoursquareIteration = pd.DataFrame(data)
192                 if len(df_FoursquareIteration) == 49:
193                     limit_reached = limit_reached + 1
194                 df_FoursquareIteration["categories"] =
195       df_FoursquareIteration["categories"].apply(lambda x:
              dict(x[0])['name'])
196                 df_FoursquareIteration["lat"] =
197       df_FoursquareIteration["location"].apply(lambda x: dict(x)["lat"])
198                 df_FoursquareIteration["long"] =
199       df_FoursquareIteration["location"].apply(lambda x: dict(x)["lng"])
200                 FrameList.append(df_FoursquareIteration)
201     df_Foursquare = pd.concat(FrameList)
202     df_Foursquare.drop_duplicates(subset=['id'],keep=False)
203     if limit_reached > 0:
204         print('Limit Reached')
205         print(limit_reached)
206     columns = ['name','categories','lat','long']
```

```
207     df_culture = pd.DataFrame(df_Foursquare, columns = columns)
208     df_culture.to_csv(filename, index=False, encoding='utf-8')
209 
210 def importTransportAccess():
211     CSV_TRANSPORT_ACCESS =
212   'https://files.datapress.com/london/dataset/public-transport-accessibility-levels/
213   2018-02-20T14:44:30.58/Ward2014%20AvPTAI2015.csv'
214     try:
215         df_transport_access = pd.read_csv(CSV_TRANSPORT_ACCESS)
216     except:
217         print('Cannot open data file - Transport Access by Ward')
218     transport_access_columns = ['Ward Code','AvPTAI2015']
219     df_transport_access = pd.DataFrame(df_transport_access, columns =
            transport_access_columns)
220     df_transport_access.to_csv('datastore/TransportAccess.csv',
            index=False)
221     return(df_transport_access)
222 
223 def importJourneyTimes():
224     XLS_JOURNEYTIMES = 'files/jts0501.xls'
225     CSV_LSOA_MAPPING =
226   'https://opendata.arcgis.com/datasets/07a6d14d4a0540769f0662f4d1450bae_0.csv'
227     try:
228         df_journeys = pd.read_excel(XLS_JOURNEYTIMES, 'JTS0501',
                skiprows=6)
229     except:
230         print('Cannot open data file - JourneyTimes')
231     try:
232         df_lsoa_ward = pd.read_csv(CSV_LSOA_MAPPING)
233     except:
234         print('Cannot open data file - LSOA to Ward Mapping')
235     journey_columns = ['LSOA_code','100EmpPTt','500EmpPTt','5000EmpPTt']
236     df_journeys = pd.DataFrame(df_journeys, columns = journey_columns)
237     df_journeys['JourneyTime'] =
238   (df_journeys['100EmpPTt'] + df_journeys['500EmpPTt'] +
          df_journeys['5000EmpPTt'])/3.0
239     df_journeys = pd.merge(df_journeys, df_lsoa_ward,
            left_on='LSOA_code', right_on='LSOA11CD')
240     shapes = 'datastore/Shapes/London_Ward.shp'
241     wards = gpd.read_file(shapes)
242     df_journeys = pd.merge(wards, df_journeys, left_on='GSS_CODE',
            right_on='WD15CD')
243     df_journeys.to_csv('datastore/JourneyTimes.csv', index=False)
244 
245 
246 def importPopulationDensity():
247     CSV_POP_DENSITY=
248   'https://files.datapress.com/london/dataset/land-area-and-population-density-ward-and-bo
249   /2018-03-05T10:54:05.31/housing-density-ward.csv'
250     try:
251         df_pop_density = pd.read_csv(CSV_POP_DENSITY)
252     except:
253         print('Cannot open data file - Population Density by Ward')
254     df_density = df_pop_density[(df_pop_density['Year'] == 2017)]
255     density_columns = ['Code','Population_per_square_kilometre']
256     df_density = pd.DataFrame(df_density, columns = density_columns)
257     df_density.to_csv('datastore/PopDensity.csv', index=False)
```

```
258     return(df_pop_density)
259
260 def importLifeExpectancy():
261     CSV_LIFE_EX =
262   'https://files.datapress.com/london/dataset/life-expectancy-birth-and-age-65-ward
263   /2016-02-09T14:25:25/life-expectancy-ward-at-Birth.csv'
264     try:
265         df_expectancy = pd.read_csv(CSV_LIFE_EX)
266     except:
267         print('Cannot open data file - Life Expectancy by Ward')
268     df_life_ex = df_expectancy[(df_expectancy['Geography'] == 'Ward')]
269     lifeex_columns = ['Ward','2010-14;Female;Life expectancy at
            birth','2010-14;Male;Life expectancy at birth']
270     df_life_ex = pd.DataFrame(df_life_ex, columns = lifeex_columns)
271     df_life_ex.rename(columns=
272   {'Ward':'Ward_Code', '2010-14;Female;Life expectancy at
          birth':'Female', '2010-14;Male;Life expectancy at birth':'Male'}
273   ,inplace=True)
274     df_life_ex['Life_Ex'] = (df_life_ex['Female'] + df_life_ex['Male'])/2
275     del df_life_ex['Female']
276     del df_life_ex['Male']
277     df_life_ex.to_csv('datastore/LifeExpectancy.csv', index=False)
278     return(df_life_ex)
279
280 def importChildObesity():
281     XLSX_CHILD_OBESITY =
282   'https://files.datapress.com/london/dataset/prevalence-childhood-obesity-borough/2015-09-21T
283   /MSOA_Ward_LA_Obesity.xlsx'
284     try:
285         df_childobesity = pd.read_excel(XLSX_CHILD_OBESITY,
                '2011-12_2013-14', skiprows=3)
286     except:
287         print('Cannot open data file - Childhood Obesity by Ward')
288     df_childobesity.rename(columns={'Unnamed: 13':'Obese%'},inplace=True)
289     obesity_columns = ['Geog Level','Code','LA code','Obese%']
290     df_childobesity = pd.DataFrame(df_childobesity, columns =
            obesity_columns)
291     df_obesityborough =
            pd.DataFrame(df_childobesity[(df_childobesity['Geog Level'] ==
            'LA')])
292     df_obesityborough.rename(columns={'Obese%':'BoroughObese%'},inplace=True)
293     borough_columns = ['Code','BoroughObese%']
294     df_obesityborough = pd.DataFrame(df_obesityborough, columns =
            borough_columns)
295     df_childobesity =
            pd.DataFrame(df_childobesity[(df_childobesity['Geog Level'] ==
            'Ward')])
296     df_childobesity = pd.merge(df_childobesity, df_obesityborough,
            left_on='LA code', right_on='Code')
297     df_childobesity['Obese%'].replace('s',
            df_childobesity['BoroughObese%'], inplace=True)
298     ward_columns = ['Code_x', 'Obese%']
299     df_childobesity = pd.DataFrame(df_childobesity, columns =
            ward_columns)
300     df_childobesity.to_csv('datastore/ChildObesity.csv', index=False)
301     return(df_childobesity)
302
```

```
def importIllness():
    XLSX_ILLNESS =
  'https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/467775
  /File_8_ID_2015_Underlying_indicators.xlsx'
    CSV_LSOA_MAPPING =
  'https://opendata.arcgis.com/datasets/07a6d14d4a0540769f0662f4d1450bae_0.csv'
    try:
        df_illness = pd.read_excel(XLSX_ILLNESS, 'ID 2015 Health Domain')
    except:
        print('Cannot open data file - Illness by Ward')
    try:
        df_lsoa_ward = pd.read_csv(CSV_LSOA_MAPPING)
    except:
        print('Cannot open data file - LSOA to Ward Mapping')
    df_illness =
  pd.merge(df_illness, df_lsoa_ward, left_on='LSOA code (2011)',
      right_on='LSOA11CD')
    shapes = 'datastore/Shapes/London_Ward.shp'
    wards = gpd.read_file(shapes)
    df_illness = pd.merge(wards, df_illness, left_on='GSS_CODE',
        right_on='WD15CD')
    df_illness.to_csv('datastore/Illness.csv', index=False)
    return(df_illness)
```

```

JavaScript for Map
<!DOCTYPE html>
<html>
<head>

  <title>London Ward Real Estate Wellbeing Map</title>

  <meta charset="utf-8" />
  <meta name="viewport" content="width=device-width, initial-scale=1.0">

  <link rel="shortcut icon" type="image/x-icon"
      href="docs/images/favicon.ico" />

    <link rel="stylesheet"
        href="https://unpkg.com/leaflet@1.3.4/dist/leaflet.css"
        integrity=
  "sha512-puBpdR0798OZvTTbP4A8Ix/l+A4dHDD0DGqYW6RQ
  +9jxkRFclaxxQb/SJAWZfWAkuyeQUytO7+7N4QKrDh+drA==" crossorigin=""/>
    <script src="https://unpkg.com/leaflet@1.3.4/dist/leaflet.js"
        integrity=
  "sha512-nMMmRyTVoLYqjP9hrbed9S
  +FzjZHW5gY1TWCHA5ckwXZBadntCNs8kEqAWdrb9O7rxbCaA4lKTIWjDXZxflOcA
  ==" crossorigin=""></script>
  <style>
    html, body {
      height: 100%;
      margin: 0;
    }
    #map {
      width: 1600px;
      height: 800px;
```

```
29      }
30    </style>
31    <style>#map { width: 1600px; height: 800px; }
32  .info { padding: 6px 8px; font: 14px/16px Arial, Helvetica, sans-serif;
33    background: white; background: rgba(255,255,255,0.8); box-shadow: 0 0
34    15px rgba(0,0,0,0.2); border-radius: 5px; } .info h4 { margin: 0 0
          5px; color: #777; }
35  .legend { text-align: left; line-height: 18px; color: #555; }
36  .legend i { width: 18px; height: 18px; float: left; margin-right: 8px;
          opacity: 0.7; }</style>
37  </head>
38  <body>
39
40  <div id='map'></div>
41
42  <script type="text/javascript" src="dataset.js"></script>
43
44  <script type="text/javascript">
45
46    var map = L.map('map').setView([51.505,-0.09], 11);
47
48    L.tileLayer('https://api.tiles.mapbox.com/v4/{id}/{z}/{x}/{y}.png?access_token
49    =pk.eyJ1IjoiYmVuY2FuZHkiLCJhIjoiY2pscXo5N3drMHFrMDNwcGxpdmUwcXA0ZyJ9
50    .nnn7Bw_KCQa2ycSTwBXq1A', {
51      maxZoom: 18,
52      attribution: 'Map data &copy;
53        <a href="https://www.openstreetmap.org/">OpenStreetMap</a>
              contributors, ' +
54        '<a
              href="https://creativecommons.org/licenses/by-sa/2.0/">CC-BY-SA</a>,
              ' ,
55      id: 'mapbox.light'
56    }).addTo(map);
57
58
59    // control that shows state info on hover
60    var info = L.control();
61
62    info.onAdd = function (map) {
63      this._div = L.DomUtil.create('div', 'info');
64      this.update();
65      return this._div;
66    };
67
68    info.update = function (props) {
69      this._div.innerHTML = '<h4>London Median House Prices by Ward</h4>'
            + (props ?
70        '<b>' + props.NAME + '</b><br />' +
71        '<b>' + props.BOROUGH + '</b><br />' +
72        props.Median_Price.toLocaleString("en-GB", {style: "currency",
              currency:
73        "GBP", minimumFractionDigits:0}) + ' Median House Price' +
74        '<br />' + props.predicted.toLocaleString("en-GB", {style:
              "currency", currency:
75        "GBP", minimumFractionDigits:0}) + ' Projected Median House Price'
              +
76        '<br />' + props.quintile + ' Quintile' +
```

```
77      '<br />' + props.Logistic + ' Projected Quintile (Logistic
            Regression)' +
78      '<br />' + props.NeuralNetwork + ' Projected Quintile (Neural
            Network)' +
79      '<br />' + props.Education_Employment.toFixed(0) + ' Education and
            Employment' +
80      '<br />' + props.Safety_Security.toFixed(0) + ' Safety and
            Security' +
81      '<br />' + props.Environment.toFixed(0) + ' Environment' +
82      '<br />' + props.Vitality_Participation.toFixed(0) + ' Community
            Vitality and Participation' +
83      '<br />' + props.Infrastructure.toFixed(0) + ' Infrastructure' +
84      '<br />' + props.Health.toFixed(0) + ' Health'
85      : 'Hover over a ward');
86  };
87  info.addTo(map);
88  // get color depending on median house price value
89  function getColor(d) {
90    return d > 1500000 ? '#800026' :
91        d > 1000000 ? '#BD0026' :
92        d > 800000 ? '#E31A1C' :
93        d > 600000 ? '#FC4E2A' :
94        d > 400000  ? '#FD8D3C' :
95        d > 200000  ? '#FEB24C' :
96        d > 0   ? '#FED976' :
97              '#FFEDA0';
98  }
99  function style(feature) {
100   return {
101     weight: 2,
102     opacity: 1,
103     color: 'white',
104     dashArray: '3',
105     fillOpacity: 0.7,
106     fillColor: getColor(feature.properties.Median_Price)
107   };
108 }
109 function highlightFeature(e) {
110   var layer = e.target;
111   layer.setStyle({
112     weight: 5,
113     color: '#666',
114     dashArray: '',
115     fillOpacity: 0.7
116   });
117   if (!L.Browser.ie && !L.Browser.opera && !L.Browser.edge) {
118     layer.bringToFront();
119   }
120   info.update(layer.feature.properties);
121 }
122 var geojson;
123 function resetHighlight(e) {
124   geojson.resetStyle(e.target);
125   info.update();
126 }
127 function zoomToFeature(e) {
128   map.fitBounds(e.target.getBounds());
```

```
129   }
130   function onEachFeature(feature, layer) {
131     layer.on({
132       mouseover: highlightFeature,
133       mouseout: resetHighlight,
134       click: zoomToFeature
135     });
136   }
137   geojson = L.geoJson(dataset, {
138     style: style,
139     onEachFeature: onEachFeature
140   }).addTo(map);
141   var legend = L.control({position: 'bottomright'});
142   legend.onAdd = function (map) {
143     var div = L.DomUtil.create('div', 'info legend'),
144       grades = [0, 200000, 400000, 600000,
145             800000, 1000000, 1200000, 1400000],
146       labels = [],
147       from, to;
148     for (var i = 0; i < grades.length; i++) {
149       from = grades[i];
150       to = grades[i + 1];
151       labels.push(
152         '<i style="background:' + getColor(from + 1) + '"></i> ' +
153         from + (to ? '&ndash;' + to : '+'));
154     }
155     div.innerHTML = labels.join('<br>');
156     return div;
157   };
158   legend.addTo(map);
159 </script>
160 </body>
161 </html>
```

Bibliography

Agafonkin, Vladimir (2017). URL: https://leafletjs.com/examples/choropleth/.

Bettencourt, Luís M. A. et al. (2010). "Urban Scaling and Its Deviations: Revealing the Structure of Wealth, Innovation and Crime across Cities". In: *PLoS ONE* 5.11. DOI: 10.1371/journal.pone.0013541.

Bhutan Studies, Centre for (2011). URL: https://ophi.org.uk/policy/national-policy/gross-national-happiness-index/.

esri (2017). URL: https://hub.arcgis.com/pages/open-data.

Foursquare (2018). URL: https://foursquare.com/about.

GLA (2014). *the Mayor of London and the London Assembly*. URL: https://data.london.gov.uk/dataset/london-ward-well-being-scores.

— (2018). *the Mayor of London and the London Assembly*. URL: https://data.london.gov.uk/.

Hristova, Desislava, Luca M. Aiello, and Daniele Quercia (2018). "The New Urban Success: How Culture Pays". In: *Frontiers in Physics* 6, p. 27. ISSN: 2296-424X. DOI: 10.3389/fphy.2018.00027. URL: https://www.frontiersin.org/article/10.3389/fphy.2018.00027.

Lyubomirsky, Sonja, Laura King, and Ed Diener (2005). "The Benefits of Frequent Positive Affect: Does Happiness Lead to Success?" In: *Psychological Bulletin* 131.6, 803–855. DOI: 10.1037/0033-2909.131.6.803.

MappingLondon.co.uk (2018). URL: http://mappinglondon.co.uk/.

OECD (2016). *Well-being in Danish Cities - en*. URL: http://www.oecd.org/publications/well-being-in-danish-cities-9789264265240-en.htm.

— (2017). *How's life?* URL: http://www.oecdbetterlifeindex.org/.

Pareto, Adriano (Apr. 2013). "Methods for Constructing Composite Indices: One for All or All for One?" In: LXVII, pp. 67–80.

Quattrone, Giovanni et al. (2016). "Who Benefits from the "Sharing" Economy of Airbnb?" In: *Proceedings of the 25th International Conference on World Wide Web, WWW 2016, Montreal, Canada, April 11 - 15, 2016*, pp. 1385–1394. DOI: 10.1145/2872427.2874815. URL: http://doi.acm.org/10.1145/2872427.2874815.

Quercia, Daniele, Luca Maria Aiello, and Rossano Schifanella (2016). "The Emotional and Chromatic Layers of Urban Smells". In: *CoRR* abs/1605.06721. arXiv: 1605.06721. URL: http://arxiv.org/abs/1605.06721.

Ratcliffe, Anita (2013). "Wealth Effects, Local Area Attributes, and Economic Prospects: On the Relationship between House Prices and Mental Wellbeing". In: *Review of Income and Wealth* 61.1, 75–92. DOI: 10.1111/roiw.12075.

RCA (2014). *The Great British Public Toilet Map*. URL: https://www.toiletmap.org.uk/.

Toronto, City of (2018). *Neighbourhoods and Communities*. URL: https://www.toronto.ca/city-government/data-research-maps/neighbourhoods-communities/.

Waterloo, University of (2017). *Home | Canadian Index of Wellbeing*. URL: https://uwaterloo.ca/canadian-index-wellbeing/.

Zoopla (2018). *Heatmap of UK property values*. URL: https://www.zoopla.co.uk/heatmaps/.