COVID 19 – Socio-Economic Factors in the UK

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**Abstract**—Put here a brief summary of your work: analysis task, data, approach, main findings. Length: up to 200 words.

# Problem Statement (250)

Here we will be looking at the COVID-19 statistics and comparing the spread of the virus in different areas and using the last census data to try to understand the various factors behind the spread of the virus.

To solve this problem, we have the COVID 19 case, death and Vaccine rates by UK region [2]. The ONS estimated age breakdown by region (as of August 2021). COVID 19 cases by age and region. A portion of the 2011 Census data showing the shared/unshared dwellings, number of cars, long term health and household deprivation [1]. Ideally, we would be using the 2021 census data, but it will not be released until 2023. We also have the geographic boundaries of the UK Local governments [11], so that we can plot this data onto a map.

We will look at the overall trends of the virus spread. Then look at various local risk factors and how they may interact with the spread, mortality and vaccination rates. Then look at whether we can make a predictive model for the virus spread at the Local authority level.

# State of the Art (500)

In the Office of National Statistics paper [8] the authors look at the breakdowns of the COVID 19 deaths by different ethnic groups and gender. The article links individuals’ census and NHS records (patient register and pandemic planning dataset) and looks at other health conditions the individuals might have. The authors were looking to get a risk factor for different ethnic groups for how likely they are to die of COVID 19. As we will not have access to census or medical records at the individual level, we can use their raw results or just use the ethic group data at the local authority level. They also break the model down by local authority district to account for any geographic variation. From this paper we have learnt that there are links between ethnic groups and COVID 19 mortality and we have a risk factor for these groups. They use various visualisations to show the differing rates of death between different ethnic groups. The paper makes some assumptions in linking NHS records to census data where there was not a direct link. For the district level data, they assume that the 2011 census records are still relevant.

Within this paper [9] from IEEE, the authors look at clustering US counties by various socio-economic factors and building time series forecasting models. They use various visualisations in their approach to decide upon how many clusters to use. They used GDP data and population breakdowns for US counties along with infection data. To cluster the counties, they used the k-means algorithm. They then compared ARIMA (auto-regressive integrated moving average) against Seasonal Trend Random Walk models to see which performed better, concluding that ARIMA was better. Their data is not usable due to being the wrong country, but their methods of normalising age and other data is very useable. One of their assumptions was that the 2019 socio-economic data could be used.

From one of SAGE’s reference papers [10] from February 2020 the authors were attempting to make a mathematical model to predict potential spreads of COVID 19 at the electoral ward level, based upon an earlier theoretical model. The authors use the 2011 census data and early infection data from the UK and China to predict potential infection rates in different parts of England and Wales. As almost two years’ worth of actual data is now available, we can use that rather than theoretical spread data. The authors have generated various visualisations of the virus transmission data. The authors separated the data out into the main regions of England and Wales, so we can see that our idea of looking at the lower-level data is valid. This paper assumed that COVID 19 would behave much the same as the theoretical virus merged with the early infection data.

# Properties of the Data (500)

Our COVID-19 case data [2] is at the local authority level (LTLA) from the results of PCR tests and positive lateral flow tests (which are reported, from 21/10/20). This data is collected from the various local authorities and then checked and published by Public Health England. The data itself is 8 columns by 244,442 rows from 13/3/20 to 28/12/21, with at least one row per day. There is an issue with the data for 1/7/20, which appears to be a correction for earlier data points. Generally, the aggregated local authority data matches the UK wide data, but does not face the same level of scrutiny as the UK wide data (being presented by the Prime Minister).

The data we have from the census [1] is at the same level, but some of the councils have been merged or split apart. Using Excel [4] we investigated the differences in councils, for the new merged councils we summed together their census data and for those splitting apart (Suffolk) we divided the data equally between them. We used Python’s Pandas library [5] to join up all of the census tables into one sheet. The census data was collected through questionnaires presented to every household in the UK. These were then aggregated by the Office of National Statistics. This dataset has 95 columns and 343 rows.

Finally, we have the local authority boundary data for 2020 from [11], which is from the ONS. This dataset has the various local authorities and their geographic properties.

The three datasets are joined together by their geography code. By plotting the cases over time using Tableau [12], we could see any obvious anomalies in the case data, such as the giant peak on 1/7/20 which isn’t replicated in the UK wide data (plotted underneath the data, in figure 1).



Fig. -District versus UK wide cases

On a similar plot (fig 2) we can see that some individual districts have anomalous spikes in cases (either due to not releasing figures over the weekend or reporting delays).



Fig. - District cases

By looking at the data in Excel we can see many days with zero cases for regions (27k in total) and other cells with null values.

To account for the noise in the case data we could move from a daily resolution to a weekly resolution.

# Analysis

## Approach (500)

First paragraph...

Following paragraphs...

*<500 words, 1 diagram*

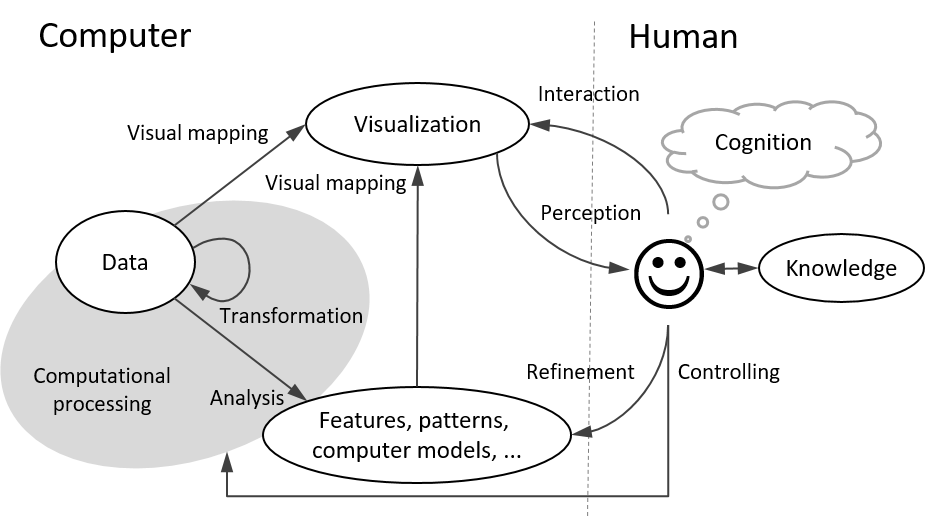


Fig. 1. An example of including a diagram in the document.

## Process (1500)

First paragraph...

Following paragraphs...

*<1500 words, <=7 images*

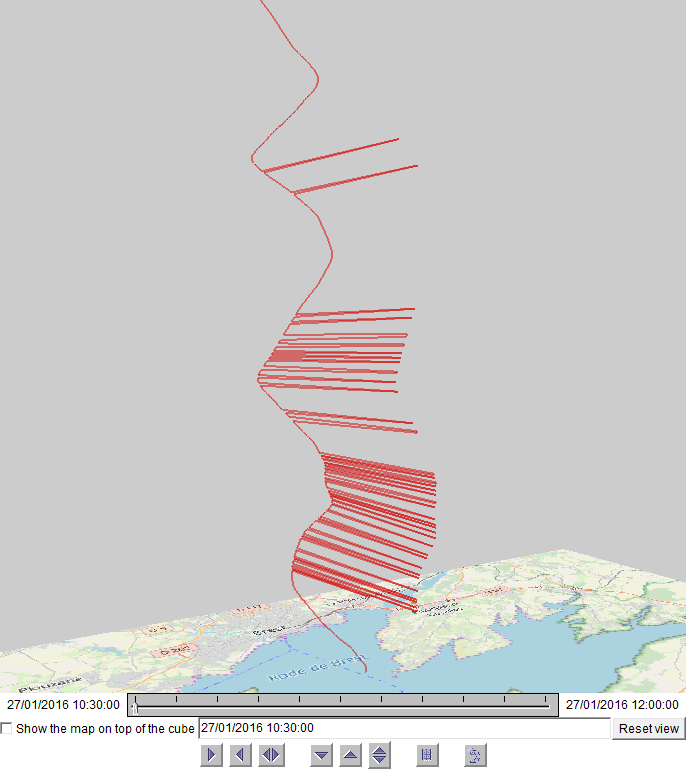


Fig. 2. An example of including a screenshot in the document.

## Results (200)

First paragraph...

Following paragraphs...

*<200 words, <=2 images*

# Critical reflection (500)

First paragraph...

Following paragraphs...

*<500 words*

Table of word counts

|  |  |
| --- | --- |
| Problem statement | 183 |
| State of the art | 463 |
| Properties of the data | 500 |
| Analysis: Approach | 500 |
| Analysis: Process | 1500 |
| Analysis: Results | 200 |
| Critical reflection | 500 |

References

The list below provides examples of formatting references.

1. Office for National Statistics; National Records of Scotland; Northern Ireland Statistics and Research Agency (2017): 2011 Census aggregate data. UK Data Service (Edition: February 2017). DOI: http://dx.doi.org/10.5257/census/aggregate-2011-2
2. Gov.UK Coronavirus. ‘Cases in the UK | Coronavirus in the UK’. HTML, 2021. <https://coronavirus.data.gov.uk/details/cases?areaType=overview&areaName=United%20Kingdom>.
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4. ‘Microsoft Excel Spreadsheet Software | Microsoft 365’. Accessed 30 December 2021. <https://www.microsoft.com/en-us/microsoft-365/excel>.
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10. Danon, Leon, Ellen Brooks-Pollock, Mick Bailey, and Matt Keeling. ‘A Spatial Model of CoVID-19 Transmission in England and Wales: Early Spread and Peak Timing’, 14 February 2020. <https://doi.org/10.1101/2020.02.12.20022566>.
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12. Tableau Software. ‘Tableau: Business Intelligence and Analytics Software’. Tableau. Accessed 1 January 2022. <https://www.tableau.com/node/62770>.