Department of Informatics University of Leicester

CO7201 Individual Project

Mine, Analyse and Visualise Healthcare Data

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Final Report (draft)

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Abstract

In the modern world, one of the main challenges for organizations and communities is the huge volumes of data available. In past decade, with data being made publicly available via open platforms, the challenge has increased manifold. With the advent of technology, governments are working towards digitization and providing effective healthcare to comply with set processes and policies. With their implementation, vast amounts of data are captured at several levels. This data can contain vital insights and clues for the decisions to be made for a better future. However, the systems available can only be used view the data in isolation and there is a need to develop a methodology, models and systems to explore the data in broader perspective. There is a dire necessity of systems which can help key personnel and stakeholders within an organization to explore the data effectively, independently to assist in quick decision making and help them to induce an amendment or propose new policies.

This project dwells into this challenge of high volumes of data for healthcare domain. Specifically, the focus is on practice level prescription data available from NHS. With the help of various data mining and exploration techniques, it investigates various healthcare datasets. The initial focus is to discover correlations between them, followed by in-depth analysis to explore the hidden insights in a broader spectrum. The report also details the data model for per-patient cost and the challenges. It is followed by the details of the web application prototype developed, its design and architecture based on the domain knowledge accumulated as part of the project. The report concludes with the learnings, outcomes and details the future developments.

Acknowledgements

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Introduction

This document is a final report generated as part of MSc individual project work for the CO7201 module. The document details the project's main aim and objectives. It then discusses the background and work done related to the topic under consideration. As part of the background, it covers several aspects such as published articles related to the healthcare data & visualization, existing systems, technologies or frameworks available for data analysis and visualization. Later different project and software requirements are discussed. It also details the status of the requirements and challenges faced to deliver them.

The primary focus is on practice level prescription data available from NHS digital. Next section, gives a detailed account of the approaches considered for data exploration, analysis and visualization. Further to the approach, the next part details the design and architecture of the web application. It is followed by the brief conclusion and future developments identified by the author. One thing to note is the project involves the application of data science principles and web application development principles. The author is a software engineer by experience, it is the project is an opportunity for the author to apply data science principles learnt, discover the insights and discuss the findings.

Aims and Objectives

The aim of the project is to analyze prescription data and correlate with other healthcare datasets available in public. The report details the datasets available and the ones considered for analysis as part of the project.

The initial objective is to explore the datasets available and then build on top of it to find the prescription behaviours by General Practices and discover rationale. The other core objective is to visualize the prescription costs data along with other datasets. The aim is to help the personnel in clinical commission groups (CCG) in elaborate analysis and decision making.

The project takes a phased approach and focuses on drug groups provided for Diabetes disease to generate insights for specific behaviours between CCGs or GPs. The outcome of the project is an understanding of the datasets independent of GPs with their prescription data i.e. it details the independent and dependent variables linked to GP prescription data. The domain knowledge of the data and their insights form are core part of project's outcome. The insights discovered during the project are detailed. Based on the datasets and their correlation, further learning about the data is done using cluster analysis. Each of the clusters formed is analyzed individually to discover a general practice's behaviour around prescriptions and related costs.

The application developed provides an intuitive way to look at a general practice with aspects of patient size profile, health profile and prescription profile with respect to the specific drug groups linked to Diabetes. The application-built forms a base framework or a platform to incorporate newly related datasets to give a combined view of the correlations formed.

The report details the challenges faced in the process of applying data science principles especially in the areas of finding independent and dependent variables to find out specific segmentation amongst General Practices. It also highlights the challenges faced and changes in initial scope and actual outcomes from the software application built.

In the end, the report details the aspects to be developed and extended in future. The insights of domain knowledge learnt can be further used with other related datasets in future to extend the model and broaden the application of them.

Project Overview

Background

Healthcare Data

Historically the organisations within healthcare domain were bound by policies set by the government. Due to the compliance measures, they had to maintain records in several forms leading to huge volumes of data. This data can be

- Used by clinical groups to find cost-effective ways to treat patients.
- Used by public health to discover disease patterns, predict and respond to disease outbreaks proactively.
- Help GPs to do patient profile analysis to predict lifestyle changes and prescriptions required in advance. However, the latest trend is data digitization which requires developing systems to explore and discover the data in a systematic way. [1]

For this project, the focus is on the practice level prescription data. The volumes Of the data under consideration is approximate ~1 to 1.25 GB per month (with ~20 million records of prescription data). Hence its important follow a systematic way to build a methodology and application.

Second important aspect is to find how does prescription costs vary from one practice to another. Based on the study by a team of researchers in Korea [2]. A prescription for a general disease such as influenza varies based on the patient's condition. Same is applicable for the variety of diseases in general. It is also possible that several diseases might have a common set of prescription patterns. The study was to uncover these prescription patterns from a set of data to find a relationship between diseases and medicines. It also states that prescription patterns can be linked to other factors such as patient age and other independent factors. As part of this project, in addition to the prescription dataset there are other datasets related to health indicators and deprivation indicators are also considered.

The third aspect of the prescription is the usage of generic and branded medicines. The trend of medical practices is to switch back from branded to generic drugs [3]. As part of the study conducted by researchers in the USA, a patient population which was using branded drugs for certain group of medicines were identified when they switched to a generic medicine soon they were introduced. A switchback is an option available to choose a specific medicine which has same ingredients and formulae available in branded as well as generic

medicines. As part of the study, the patients who opted for generic medicines were followed to switch to branded ones. As an outcome “adjusted switchback rates were consistently lower for patients who switched from branded to authorized generic drug products compared with branded to generic drug products in the primary cohort (pooled hazard ratio 0.72, 95% confidence interval 0.64 to 0.81)” [3]. It will be essential to understand the usage of generic medicines versus branded medicines and their impact on overall prescription costs of medical practices. In line with this study, CCGs within NHS provide a “Recommendations for appropriate prescribing of generic and branded Medicines” [5] which acts as a guideline for general practitioners.

The fourth aspect is whether the competition between the GPs has any impact prescriptions. Based on the study by Catherine Schaumans, TILEC, CentER, Tilburg University, Netherlands. It is possible that a GP can prescribe all the medicines need from the pharmacy including over-the-counter as well as prescription medicines. The probable reason for this behaviour is to meet the patient’s expectations. Another aspect is the volume of prescriptions, the study mentions that “The higher the percentage of female GPs, the lower number of GP contacts (which is in line with female GPs being more likely to work part-time) and the higher the percentage GPs with a lot of experience (>20 years), the lower the consumption of primary care. Finally, the more GPs perform home visits, the higher is the consumption of care” [4]. As part of the conclusion, there are several aspects to be considered for the behaviours such as volume of prescriptions, GP competition and GP characteristics.

Data Sources

A list of data sources considered for the project are as below:

1. NHS Digital – This is a digital platform from NHS providing information systems including infrastructure for health and care. It provides several datasets in relation to prescriptions. However only below two datasets are considered for this project:
    - Practice Level Prescribing in England
    - Clinical Commissioning Group (CCG) prescribing data

    This data contains practice level data for each month within England.

    “For each practice in England, the following prescription information is presented at presentation level for each medicine, dressing and appliance that has been subsequently dispensed in the community in the UK:
    - Items - the total number of items prescribed and dispensed
    - NIC - the total net ingredient cost
    - ACT - the total actual cost
    - Quantity - the total quantity (in terms of number of tablets or millilitres, for example)” [NHS Digital]

    For each month’s data released (generally after 2 months of actual data is ready), comes with three distinct files as below:
    - “Practice Prescribing Data file” – it is the primary data file of focus with the practice level prescribing data at presentation level using the full 15-digit BNF code. This data file is larger size ~1 GB with more than 1.5 million records.

- “GP prescribing chemical substance file” – it gives the chemical substance or section as appropriate using the 9-digit (Drugs) or 4-digit (Appliances) BNF code.
- “GP prescribing practice address file” - this is a lookup data with details of the practice name and address.

As of now, GP prescribing chemical substance and GP prescribing practice address are considered as available from NHS BSA. Only the latest datasets are considered.

2. NHS Business Service Authority's Information Portal – This data source provides additional details of the practices and medical formulations i.e. BNF. As a system it has “reports and data to help NHS customers track trends, inform decisions and support policy”. Below datasets are considered:

   BNF Code Information:
   BNF Code is a unique code given to a prescription. This is a 15-digit code sub-divided into 8 sub-sections:

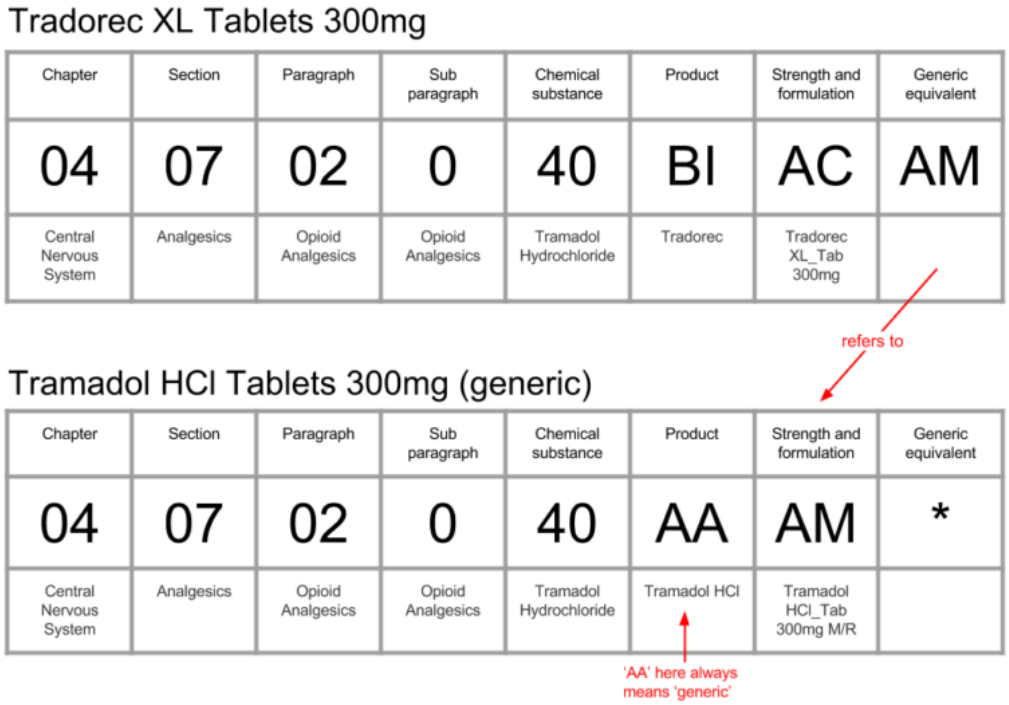


Figure 1 BNF Code Structure (source: https://ebmdatalab.net/prescribing-data-bnf-codes/)

In total there are 23 chapters with each of them linked to a specific body function. Each of the chapters is divided into section, paragraph and sub-paragraphs.

- Patient List Size Information:
  This data consists of general information about a GP such as a region information, its name, its code and more importantly age distribution of the patients as below:

General Information	Patient Age Distribution
Regional Office Name Regional Office Code	Male 0-4 Female 0-4

Area Team Name Area Team Code PCO Name PCO Code Practice Name Practice Code	Male 5-14 Female 5-14 Male 15-24 Female 15-24 Male 25-34 Female 25-34 Male 35-44 Female 35-44 Male 45-54 Female 45-54 Male 55-64 Female 55-64 Male 65-74 Female 65-74 Male 75+ Female 75+

From the patient age distribution, total patient list size of GP is calculated.

- It also provides Detailed Prescribing Information as offline data (same as – NHS Digital Prescription data)

3. Public Health Data England or FingerTips data:
   This is an important data source with information on disease prevalence and other health profile indicators for England. As a system, it provides profiles which "are a rich source of indicators across a range of health and wellbeing themes that have been designed to support JSNA and commissioning to improve health and wellbeing and reduce inequalities. With these profiles you can:
   - Browse indicators at different geographical levels
   - Benchmark against the regional or England average
   - Export data to use locally" [https://fingertips.phe.org.uk/]

   This dataset is used to link the prescription with the outcomes and effectiveness of health care policies. From this dataset following indicators are considered:

Indicator ID	Indicator	Definition
241	Diabetes: QOF prevalence (17+)	It is the percentage of patients aged 17 years+ and with diabetes mellitus, as recorded on practice disease registers.
219	Hypertension: QOF prevalence (all ages)	The percentage of patients with established hypertension, as recorded on practice disease registers (proportion of total list size).
91872	Deprivation score (IMD 2015)	Index of Multiple Deprivation Measure

There are several other indicators which can be considered in future as necessary.

Related Work

This section details the systems developed around prescription data.

1. OpenPrescribing –

This is a system developed in collaboration between several partners namely The Health Foundation, University of Oxford, NIHR and others. It also encompasses other data sources. This system provides dashboards from the perspective of a CCG and Practices. It also provides users to analyse specific formulations of interests within a CCG or Practice. It also provides a public open API - https://openprescribing.net/api/

2. http://www.prescribing.info/

This is another system built using Microsoft BI. This primarily focuses on prescription data and provides a drill-up and drill down views which is an important reference for the project.

However, the systems above do not correlate the prescription data with other datasets related age or diseases. This is crucial from the clinical questions under consideration. The need is to have a system which will allow the CCG personnel to visualize the data in a combination of different profiles.

Data Analytics

The core of this project is data mining and analysis of prescription dataset and others under consideration. As a choice there were a lot of tools/frameworks to select from, some of them are: Hadoop, MapReduce, Weka or R etc. However, the author as a preference has chosen Anaconda data science platform as a framework of choice.

Anaconda Data Science Platform

Anaconda is one of the most popular data science platforms based on Python. The version is 1.6.5.
It was selected due to the reasons below:

- Author's personal interest to learn and work using Python as a programming language
- The courses attended by the author used Python and frameworks extensively.
- More importantly, notebooks can be used to collaborate the ideas within the team. This feature was crucial to get inputs and guidance from stakeholders involved in the project.
- It provides a platform of libraries essential for analysis, visualization and machine learning

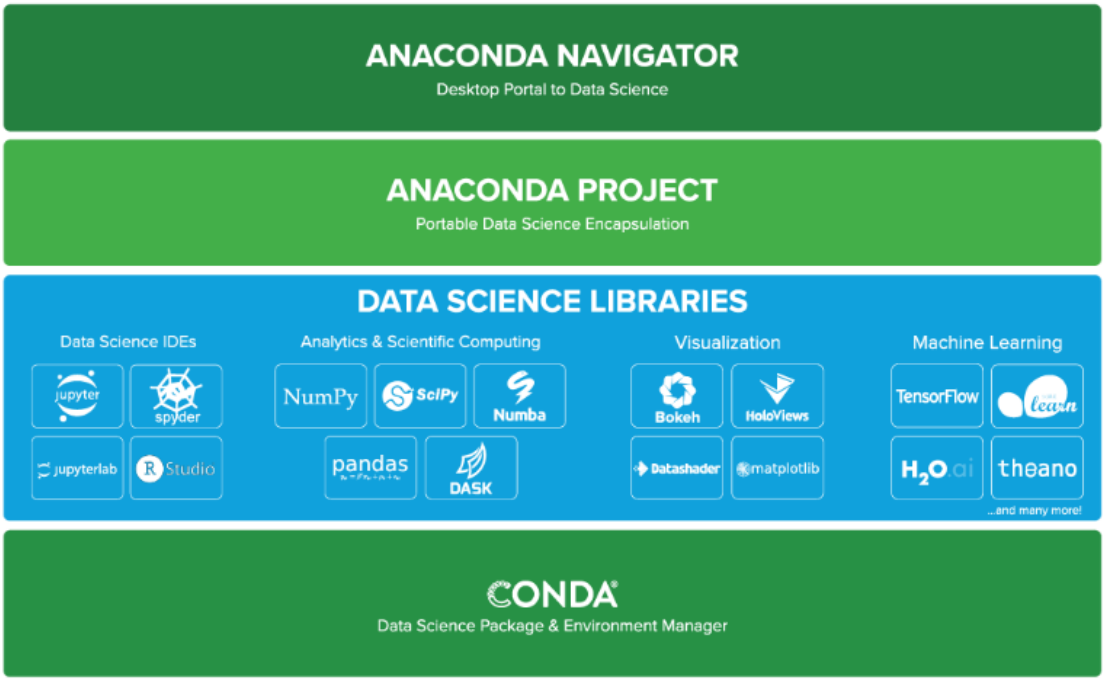


Figure 2: Anaconda Data Science Platform

(source: https://www.anaconda.com/distribution/)

Python

Python is used as a general-purpose programming language for data exploration activities. The version is 3.6.3.

SciPy

This is a python based eco-system. It encompasses following core libraries. It also provides a library for scientific and mathematical computing. The version is 0.19.1.

Pandas

This is powerful data analysis toolkit based on the platform. It allows the importing huge volumes of datasets and perform various operations on the data in the form of data frames. The version is 0.22.0.

Numpy

This library is useful in processing for numbers, strings, records and objects. It complements the Pandas toolkit for advanced operations on data being processed. The version is 1.13.3

Jupyter notebooks

This is a web-based, interactive computing notebook environment. It provides collaboration platform to share ideas as python code, markup, documentation and visualization like documents. They can be exported as HTML. The version is 5.0.0.

Orange

This is workflow-based data analysis and visualization framework. It provides a component-based data mining framework with interactive workflows and an extensive toolbox for broader data science activities. The version is 3.11.0.

Machine Learning

Next core activity of the project is to learn from the data aggregated from the various datasets. It requires the application of the various machine learning algorithm to process and discover insights. The project two distinct aspects to be covered. The first being to distinguish practices based on selected independent variables. The second is a process of generating a data model to discover a correlation between certain dependent variables to predict a target which is related to prescription cost. Thus, the project involved both supervised and unsupervised learning required from the data.

Supervised learning is a concept where the target variable is known. The process to generate a data model which could train the data to learn about the target variable and predict the output for any new data. In case of supervised learning, to build a robust data model a trained data is used to build the model and make it learn. The robustness of the model is validated with the test data and as necessary the model is fitted to be considered for prediction. With the help of this learning, the model built can make predictions for the new data and generate the target. <list techniques>

Unsupervised learning is a concept where the primary focus is to explore the data and learn from it. Unlike supervised learning, the target variables are unknown. As part of this technique, we rely on various machine learning algorithms and discover patterns from the data.

Scikit

This library provides set of modules for machine learning and data mining. It is used for unsupervised learning. As part of the project it is used within Jupyter Notebooks package with Anaconda framework. The version is 0.19.1.

Orange

Orange as a framework also provides components for applying machine learning to the data. As part of this project, this tool is used for supervised learning of the data in the form of workflow.

Data Visualization

The next vital part of this project is data visualization of healthcare data.

In a study [6] the focus was prescription behaviour for specific physicians, medicines and set of diseases. The primary entities of the study were the relationship between physician, medicine and patient. Although the work is related electronic health record visualization, the main aim was to find out the problems faced in providing user interfaces/visualizations which are intuitive and are effective for physicians. The objective was to help them understand their behaviours when providing prescriptions at different stages of consultation. Based on the findings, they had concluded set of requirements such as:

“the system must show multivariate data”
“the system must show data from multiple perspectives” to facilitate different viewpoints
“the system must enable to select entities or a time interval of interest to get relevant statistics about this selection”
“the system must facilitate comparison between these entities”.
As a solution, it also mentions about “Three table view” which gives a combined view of physicians, patients and medicines. The above requirements and “three tabled view” (3TV) forms a good base for this project.

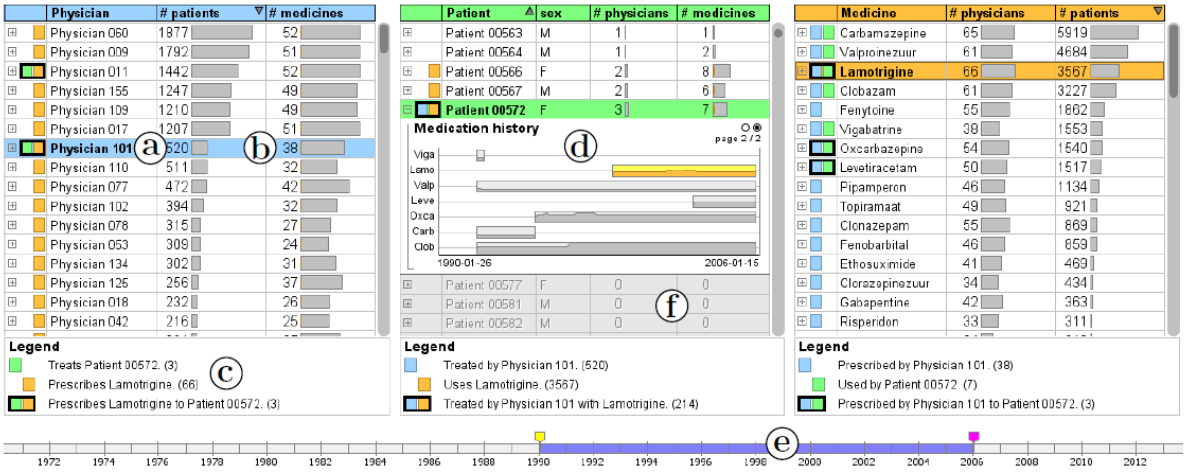


Figure 3 Three table view [6]

In a paper [7], the focus was to use “time-oriented cartographic treemaps” to show multivariate data which is hierarchical and uses space available in the most optimized way. It uses the results from the study to explore trends of health diagnoses overlaid in geospatial view. It exploits both static and animated view.
In the below view, the conventional treemap is used at geographic map level to show the data trends at CCG level.

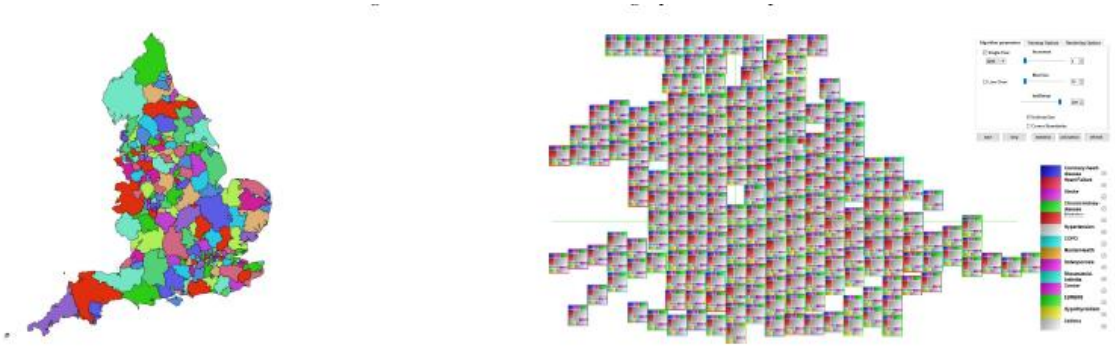


Figure 4 Cartographic Treemap is covering more space as compared to a conventional map. [7]

This is a useful reference to use the conventional visualization technique to use along with space and time complexities thus providing dynamic content.

In terms of recent advances in data visualization, a survey [8] discusses the information visualization research area which aims to helps users to explore, understand the data via visual exploration. The paper discusses, a “visualization pipeline”

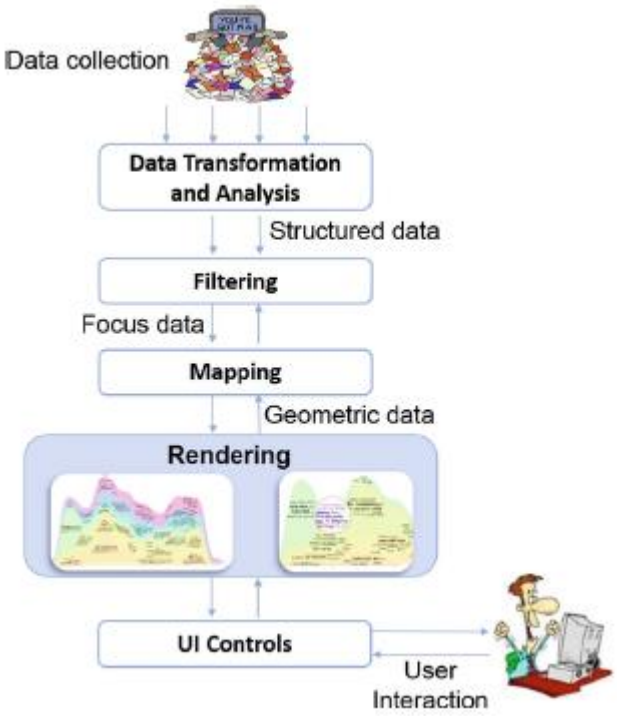


Figure 5 Visualization pipeline [8]

It suggests a structured way to handle the visualization based on the user interaction. The steps include “data transformation”, “filtering”, “mapping” and “rendering” on the UI controls. In terms of architecture for the project, the data transformation and filtering should be handled by the systems which are aware of the structure of the data whereas mapping and rendering should be handled by the layer responsible for visualization or presentation.

The survey also discusses several frameworks such as “InfoVis”, “Prefuse” etc. which are JavaScript-based and provide interactive visualizations. However, the document-driven document (D3) library is a recent and a popular web-based library. It provides direct manipulation of the document which updated the web element and drives the visualization. Using this library, the application can provide folding interactions, theme river, Stacking-based trajectory visualizations to name a few. From a development perspective, D3 is available in JavaScript and comes with a learning curve but can be incorporated into modern web application frameworks.

Plotly

Plotly is a web visualization library built on top of D3.js. It is an open-source JavaScript library used to create sophisticated and visual interactions. As a package, it provides several 2D and 3D visualization components with interactive features such as zoom, selection, save which are additions to the D3.js library. For the project, although D3.js was the initial choice for providing visualization. But as the project progressed, Plotly is selected.

2D Visualization

Under this category, the data is visualized as scatter plots, pie, radar and spider charts. In addition to Plotly, the 2D visualization was used:

- in Jupyter notebooks, “matplotlib” and “seaborn” libraries are used for visualization.
- The orange framework is also used as necessary.
- MS Office Excel using its extensive 2-D charts

3D Visualization

Under this category, the data is visualized as 3D scatter plots and 3D surface plots using Plotly library primarily.

Web Technologies

This section details the technologies selected for a web application developed for the project.

Mocks

As part of UI design, mocks are created using the draw.io. This is an online mock-creation tool and provides options to create the user interfaces using available libraries. The mocks can be shared in the form of HTML or pdf for collaboration.

ASP.Net MVC

This is the web application framework selected for the project. It implements model view controller architecture. MVC5 is used and the language is C#. .Net framework version 4.6. The framework implies usage of Bootstrap for web page styles, jQuery and JavaScript for client-side scripting. The application developed using this framework will form presentation layer of the software architecture.

Web Services

The project also involves web-services. They are introduced to abstract the interaction of the application for information retrieval from different data sources. They will be developed mostly as rest services using C#.net.

Visual Studio

Considering the technology selection for the web application is mostly Microsoft. Visual Studio 2015 will be used as an IDE for the development.

Azure

From a deployment perspective, the websites and web-services will be deployed in the Azure environment. For the project, the Azure account provided via Microsoft Imagine licence of the University is used. However, when a decision to deploy publicly appropriate environment needs to be selected.

Learning

This section details the areas of learning achieved or attempted by the author for the project. The author is software developer by experience, however the area of Data Science and Machine Learning is totally new.
As part of the project, following courses were considered for learning.

- Big Data & Predictive Analysis – CO3093 module from the University of Leicester
- edX course - Python for Data Science – This is one of the modules a part of Data Science MicroMasters program delivered by The University of California, San Diego
- Python and Anaconda Data Science Platform – Python and all the libraries & tools listed as part of Anaconda platform are learnt and used as necessary.
- Bootstrap – This project was the first instance where Bootstrap was used.
- Plotly and D3 – The javascript visualization libraries used within prototype had a steep learning curve for the project.

From a domain perspective, the prescription data domain and related topics explored during the project were new. The topics include various healthcare data sources at a high level, prescription data, BNF, public health profiles and indicators The domain knowledge is vital to contribute to this topic in future beyond the project.

Requirements

This section details the requirements considered for the project their status and any remarks if any.

Data Mining

The table below is the initial set of requirements detailed in the preliminary report of the project.

Req. ID	Requirement Description	Status	Remarks
Essential – Priority 1			
D-1	Define data sets and the parameters for consideration	Achieved	
D-2	To prepare localized data sets for pilot	Achieved	
D-3	Explore the data sets with reference to clinical questions under consideration	Achieved	
D-4	Explore and generate correlations of data sets	Achieved	
D-5	A set of clinical questions to be considered in the order of priority are as below: Practices - Patient Size and Prescription cost variation	Achieved	
D-5-a	Practices level insights with respect prevalence of drugs and diseases	Partial	Only for Diabetes and Drug Groups provided by Prof. Umesh
D-5-b	CCG level view - practices & prevalence of drugs	Partial	Data exploration only.
Essential – Priority II			

D-6	Develop a methodology and generate a model to normalize, visualize and correlate the data	Achieved	Normalization and Cluster Analysis
D-7	Visualizations for correlations	Achieved	3D Cluster Analysis and further analysis
D-8	Export the correlated data in visually rich formats o Combining Patient Size, Prescription Volume and Patient Distribution to bring insights	Achieved	2D Scatter plot covers five dimensions - x-axis parameter - y-axis parameter - size of the dot - the colour of the dot - the shape of the dot
Recommended			
D-9	Cost per head calculation and its relation to patient size and prescription volume	Achieved	Per patient cost was analysed as part of the data model. It's relation to other parameters concluded.
D-10	Practices - Prescription and Distribution among drug groups for ex: Diabetes Hb1Ac with Statin usage on a certain population on QoF prevalence similar to cholesterol	Partial	Only for Diabetes and Drug Groups provided by Prof. Umesh
Optional			
D-11	Develop a (used in epidemiology) technique for statistical calculation of prevalence - i.e. to develop a prevalence estimate which is age adjusted	Not Achieved	This will require further analysis and domain knowledge of datasets with respect to more profile indicators.
D-12	Build a technique to predict the demand for volume for a certain drug	Modified	Instead a model to predict per-patient cost was carried out to find out dependent variables.
D-13	3D Visualization of data from multiple datasets	Achieved	Via 3-D Cluster Analysis linked to 2-D plot and multiple tables for General Information, Costs information overall at the chapter level.

Software

The table below lists the requirements considered for the web application prototype developed as part of the project. These requirements were considered later in the project, due to the fact that knowledge of the domain & data during the course of the project. (Table to be updated after the demo)

Req. ID	Requirement Description	Status	Remarks
A-1	It must provide a way to search a GP or CCG using a free text		
A-2	The search pattern could be practice code, CCG code, postcode or area name		
A-3	The result of a search should show the entries with general information: practice or CCG name, code and postcode.		
A-4	Each search result item should provide two options: View or Add to Focus		
A-5	View option provides an option to view profiles of GP or a CCG		
A-6	Add to Focus provides an option to add an item to focus group for further analysis		
A-7	It must provide a specific page to visualize the clusters		
A-8	Once a cluster is selected, it should provide all the parameters to select either as a value for x or y-axes.		
A-9	The application provides an option to choose the Drug group for analysis of costs		
A-10	When visualization of GP data is shown, hovering over a GP instance should show general GP information, Total costs information, Chapter and Sub information		
A-11	When a drug group is selected, and a GP is clicked on the plot. The application must show a pie-chart with the distribution of formulations.		
A-12	When a GP is viewed it should show all the profiles general, patient list and health profiles.		
A-13	When GP is viewed, it could provide an option to view the costs trend for a specific drug group or total for each month across the year		
A-14	When a focus group is viewed, it should show all the profiles applicable to group		

Approach

This section details the approaches considered for data mining and analysis of the datasets. It gives detailed step-by-step activities taken for the core part of the project.

Data Exploration

Data Exploration started with the process of finding the offline data for the datasets under consideration. All of the datasets were available in CSV format as direct links or downloaded via a Web interface.

Prescription Data

Considering the data volume, the practice level prescription data was localized for a CCG. The CCG selected was Q59 of Leicestershire and Lancashire. So “Area Code”

was used as a filter. The localized data was used as a basis for understanding. Some of the highlights are as below:

- It contains individual prescriptions for each of the practices. However for the same presentation, the data is not aggregated as assumed.
- To find chapter and sub-chapter level costs, the data needs to be updated with additional columns chapter and sub-chapter. Once this information is added, the data can be grouped at chapter and sub-chapter level to find the aggregates.

The required aggregation of data was carried out within Jupyter notebooks.

As part of exploration for a specific disease, Diabetes was considered and related drug groups:

- 0601021* Oral hypoglycaemics
- 0601022* Metformin
- 0601023* Gliptins
- 0601023AKAAA * Alogliptin - costlier options
- 0601011* Insulin
- 0601012*Insulin
- 0704050* Viagra and others

GP Profile data

Next step was to consider GP related information.
Patient List size :
This gives the information about the distribution of patient ages within a practice. From this total patient size can be calculated. The average age profile of a practice was not available with the data hence it was calculated as simple formula as below:

$$Average\ Age\ Profile = \sum Number\ of\ patients\ in\ an\ age\ range * Max\ of\ age\ range \Big/ Total\ Patient\ List\ Size$$

GP count:
This information has details about GP address, postcode and a number of general practitioners available. This is an important measure to decide whether the number of GPs available have any effect on prescription behaviour and a measure of health deprivation.

Public Health Indicators & Index of Deprivation Measures

The second aspect of a general practice profile is the health profiles available from Public Health England dataset. This data is available offline in the form of CSV data as well as public API via fingertips interface.

The dataset is available annually since 2008 but it provides crucial information which covers multiple facets as below:

- Index of multiple deprivation measures
- QoF information for various diseases such as “patient count” of a specific disease can be found.
- The data also captures what is the distribution of patients w.r.t ratings of specific diseases such a Hb1Ac level, Blood Pressure levels. This is crucial to understand the trends and health profile of a specific GP or an area annually.
- GP patient data - this dataset is available as a separate public data. It provides satisfaction indicators which are generated from the surveys or feedback questionnaires filled by the patients.

- Other crucial information of interest is “% of 65+ age” patients and the number of patients with long-term illness.

Combining Datasets

As part of Data exploration, GP patient list size and GP count datasets were combined. Average age profile was introduced. The insights from this combined dataset are as below:
- at UK level - map view (to be updated)
- at Leicester level - map view (to be updated)

Next step was to find a correlation between patient list size and costs, the data for Q59 CCG was visualized.

As mentioned earlier, to find out the common factors between general practices GP patient list size along with total prescription cost (ACT cost) in were considered only for Dec. The scatter plot of total prescription costs for Dec 2017 (NHS Digital) vs Total patient list size (NHS BSA) is as below:

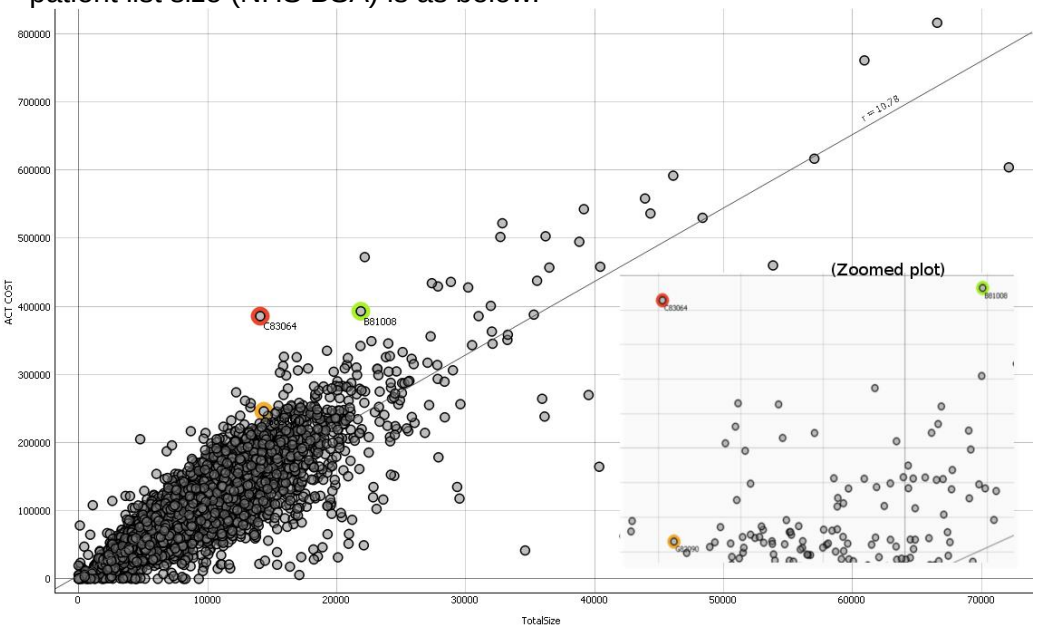


Figure 6: Scatter plot for Patient list size vs Actual Costs

As a further step, specific GPs of interest are considered combined with public health profiles, following insights were found.
- comparison of GPs with same list size but different costs
- comparison of GPs with different list sizes and similar costs

The selected GPs are: C83064, G82090, B81008. C83064 has a patient list size same as G82090 but prescription costs close to B81008

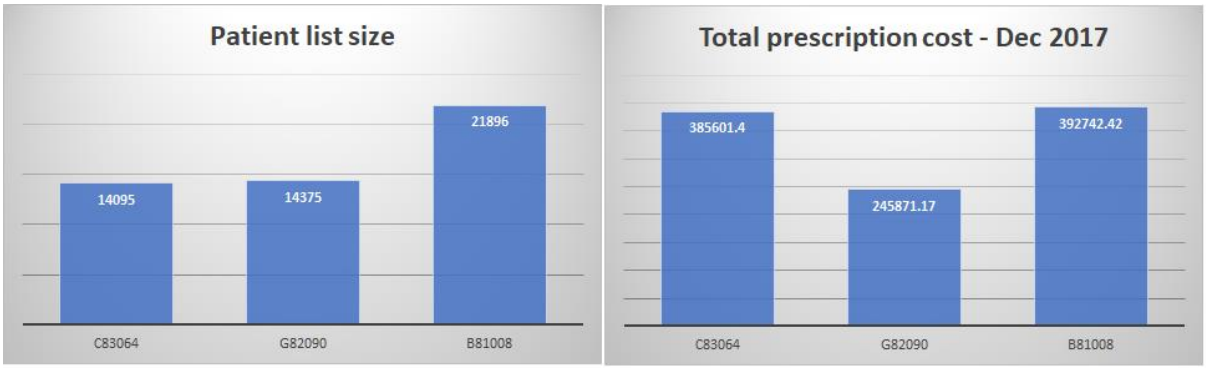


Figure 7: Comparison of patient list sizes and costs for selected practices

To understand the reasons for the variance, the distribution of patient list size, additional factors such as disease prevalence (PHE: Diabetes, CVD profiles) were considered:

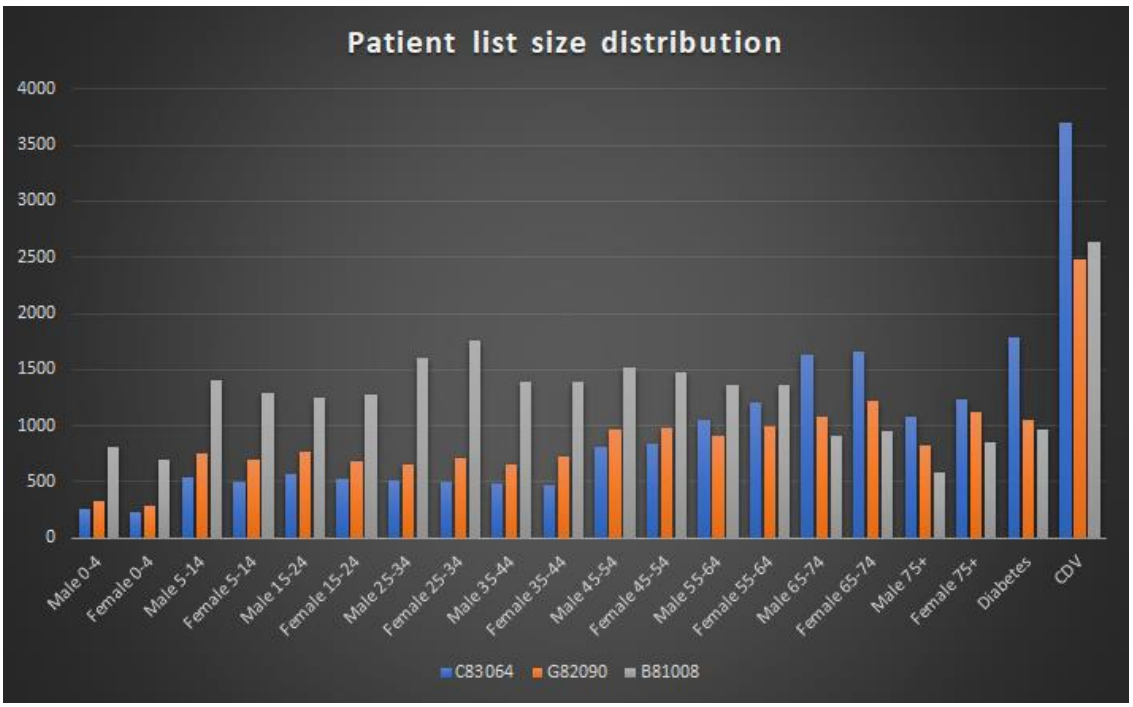


Figure 8: Distribution of patient across ages, diabetes and Cardio-vascular diseases

From the above plot, C83064 differs from other two GPs:

1. It has a higher patient list size in range 55 to 75+
2. Diabetes and Cardio Vascular Disease significantly higher than others.

To explore additional parameters, Index of multiple deprivations (PHE: IMD 2015) and GP Count (NHS BSA) were considered.

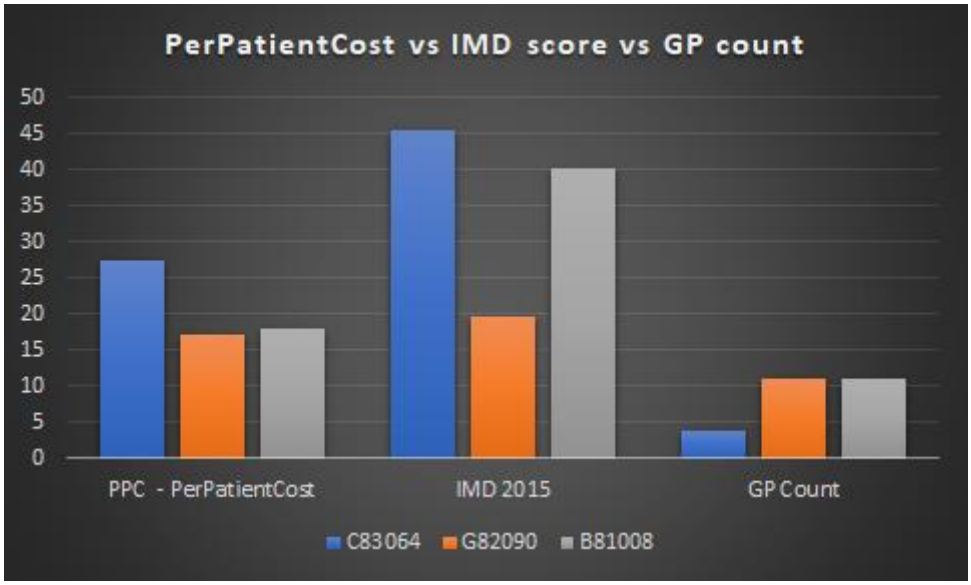


Figure 9: Per Patient Cost vs Index of Multiple Deprivation vs GP Count

From the above plot, with 19% IMD - G82090 is less deprived than C83064 which has a higher deprivation index. However, B81008 also highly deprived area but in terms of GP count, C83064 has only 4 GPs as compared to 11 in others.

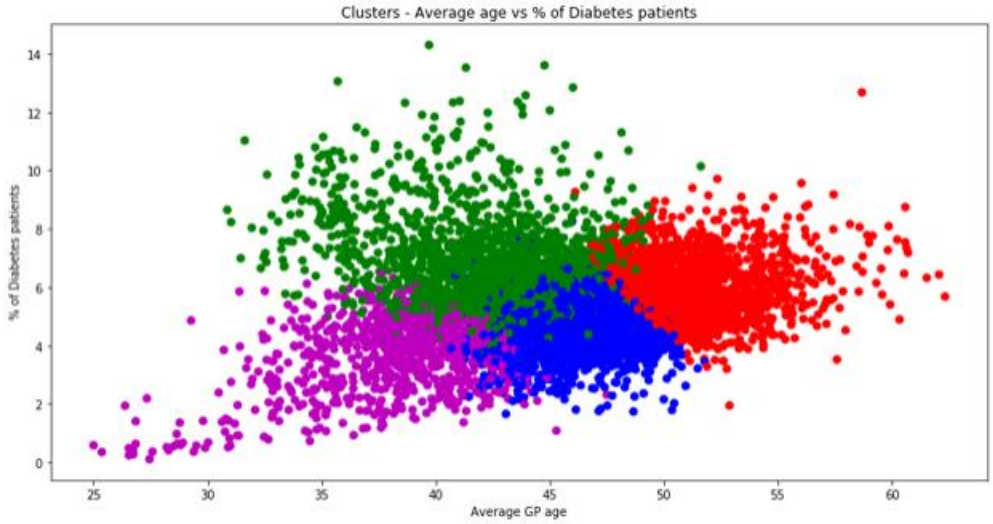
From above insights it can be concluded that merely comparing prescription data will not be enough but it requires combining this information with related datasets to find the reason of prescription cost variations.

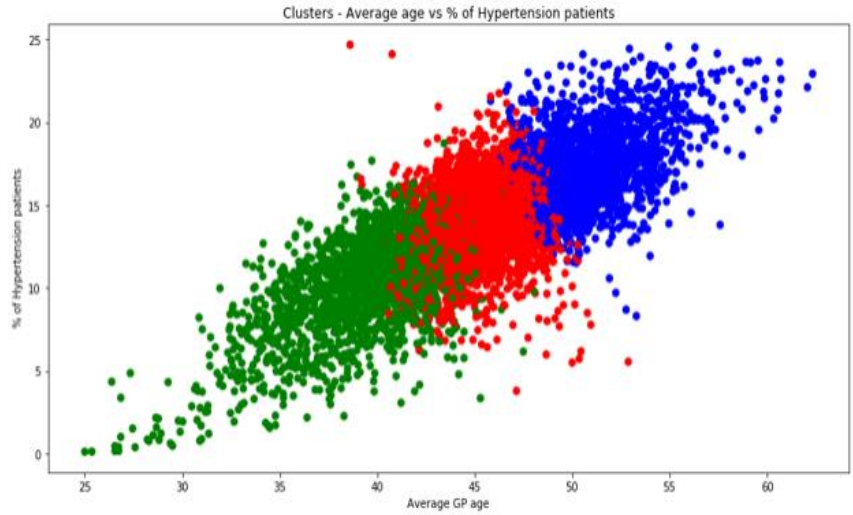
Cluster Analysis

Next step was to process the correlated data and learn about it. Since we don't have specific target defined unsupervised machine learning techniques was used.

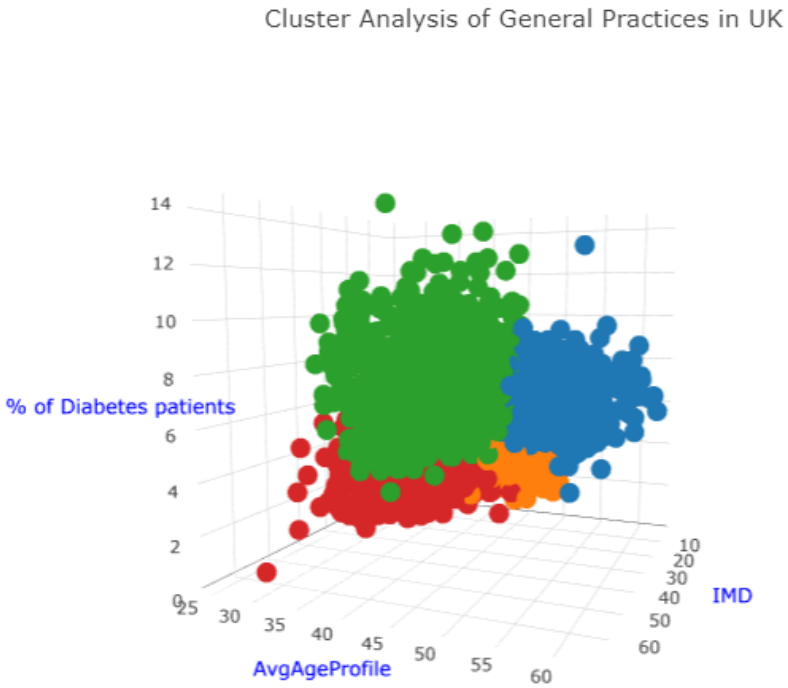
Specifically cluster analysis was used to determine segmentation based on following independent parameters: Average age profile, % of diabetic patients and index of multiple Deprivation scores. KMeans ++ algorithm is applied.

Below are the clusters for Diabetes and cardiovascular disease: Hypertension.



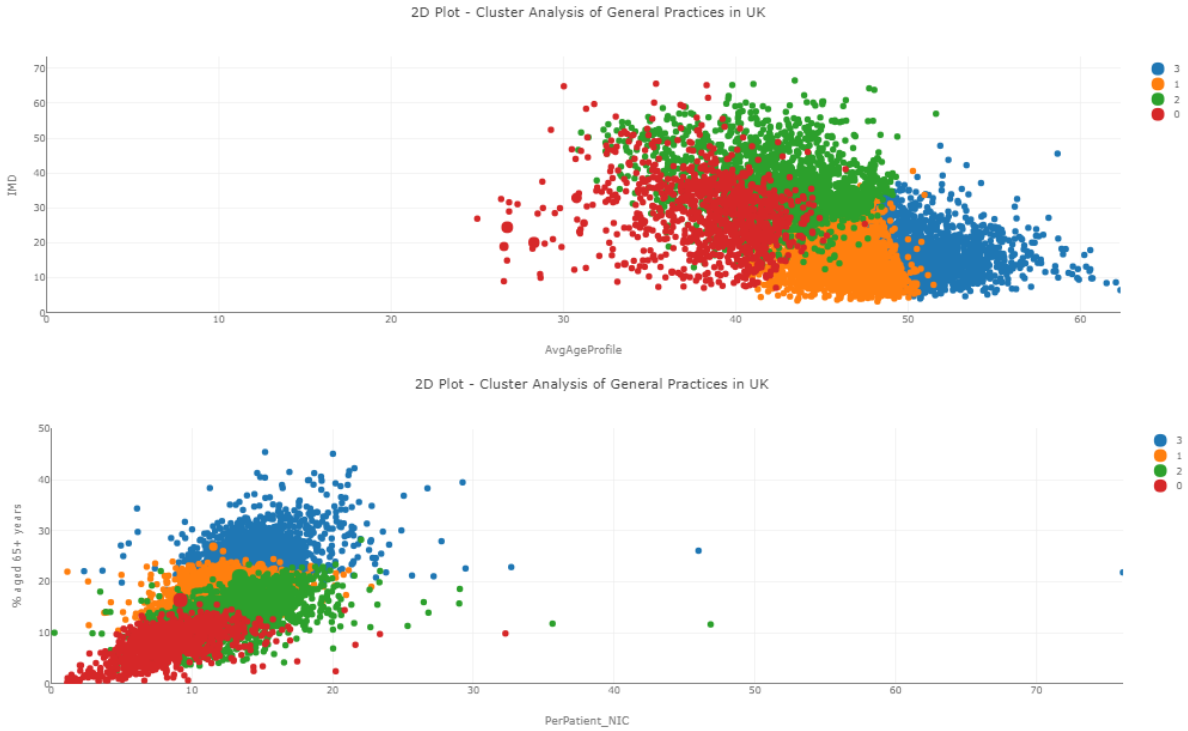


However, it was not very evident whether the clusters formed were profound. Hence 3-D visualization was carried.



Based on the above clustering, the clear indicators are age profile and deprivation measures.

In line with the clusters, when per-patient cost and % of 65+ age are considered. Following insights can be discovered:



Next step is to analyse each of the clusters to find a correlation between costs and features which define the variation between per patient costs.

As described earlier, as part of the project-specific drug groups were considered for Diabetes as a disease. Each of the clusters and costs for each drug groups was analysed. For detailed analysis the distribution of costs for drug groups was done at subchapter level w.r.t formulation names. This helped to understand the variations in prescriptions of generic or specific drugs which vary in costs thus affecting overall costs incurred by a practice.

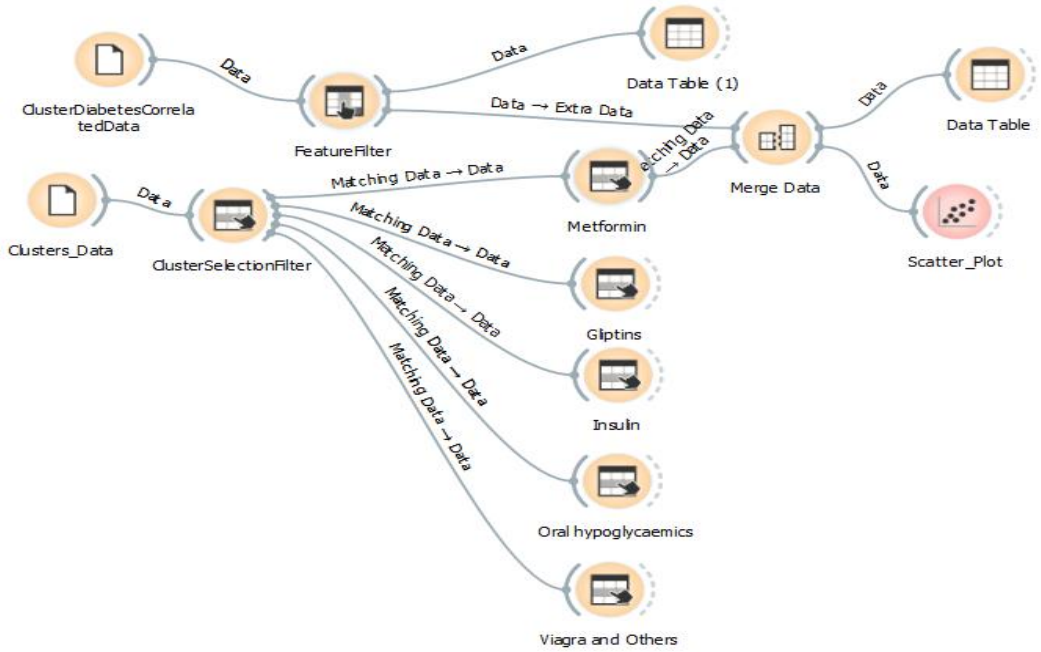


Figure 10: Generic Cluster Analysis data for selected Drug Groups

Jupyter notebooks

As part of the data exploration phase, notebooks were created for following activities:

- Prescription data pilot data
- Prescription cost comparison between 2 GPs
- Patient list size comparison between GPs
- Multiple Dataset correlations (GP, PHE, NHS BSA)
- Cluster Analysis
- Cluster Analysis - Drug group costs
- Cluster Merged Data

Data Model

	#	Univar. reg.
% of Female 75+		3544.025
% of 75+		3439.531
% aged 65+ years		3419.078
% of Male 75+		2996.560
AvgAgeProfile		2877.742
% of 65-74		2842.336
% of Female 65-74		2796.499
% of Male 65-74		2747.831
% of Female 55-64		2448.783

Figure 11: Ranking of features with a level of correlation

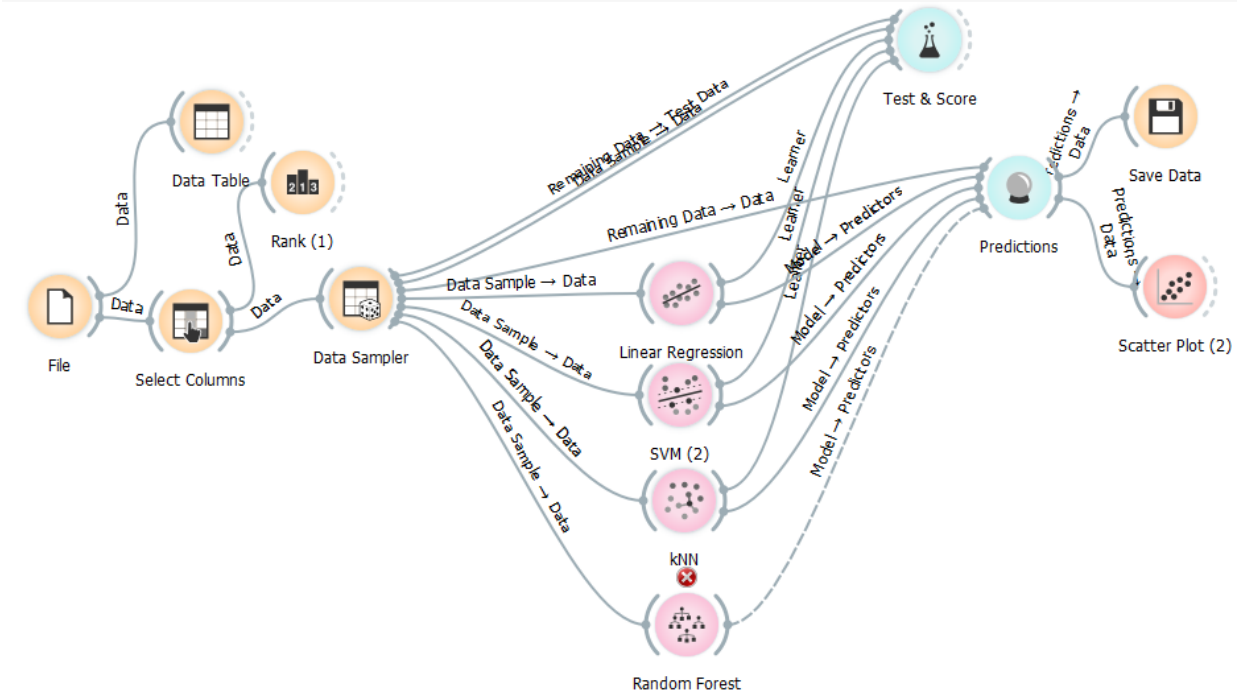


Figure 12: Data model to predict per patient cost

Challenges

Technical Specifications

This section details the proposed architecture of the application to be developed for the project. The current scope of the project might be limited, but in a long-term application needs to handle multiple datasets and handle correlation between them.

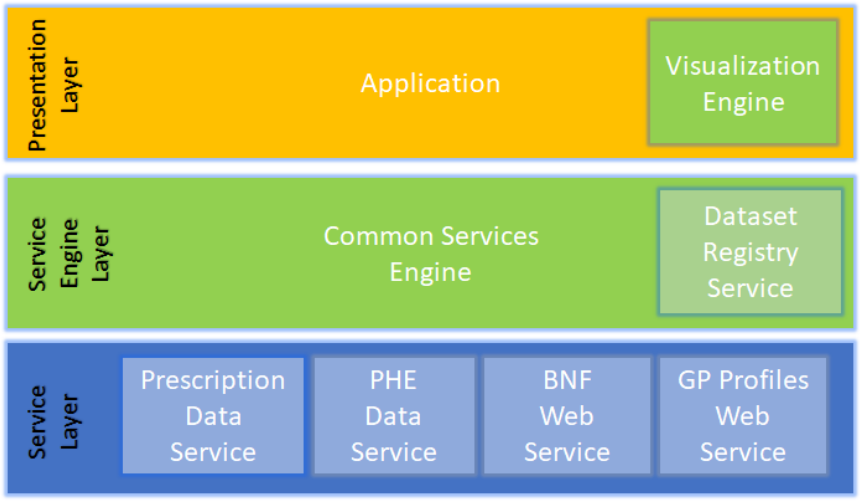


Figure 13: Software Architecture

The overview of the architecture is as below:

- The service layer represents the datasets and the web services providing the information.
- Each of the data services registers itself via Dataset Registry Service. During registration, the service will submit its schema information and as well as correlation with other datasets. If the related datasets available, the correlation information will be used. Each of the data services will be a rest API service, so that if required it can be deployed as public API.
- The registry service is an integral part of common services engine. Through this service any new dataset service can be registered.
- The common service engine abstracts the communication with actual datasets and their services from the application perspective.
- Since the application is built on MVC framework. Only controllers will be responsible for communicating with common services engine.
- Visualization engine has the intelligence to build data visualization and is used by Views of the application. It abstracts all the complex logic to create document driven documents required as part of the plotly.js library.

Application prototype

Wireframes

Based on the areas of interest for the prescription data and related datasets the mock screens were generated. They are detailed in following sections.

The screen below shows the search screen and results returned with the option to view trends and Add to focus.

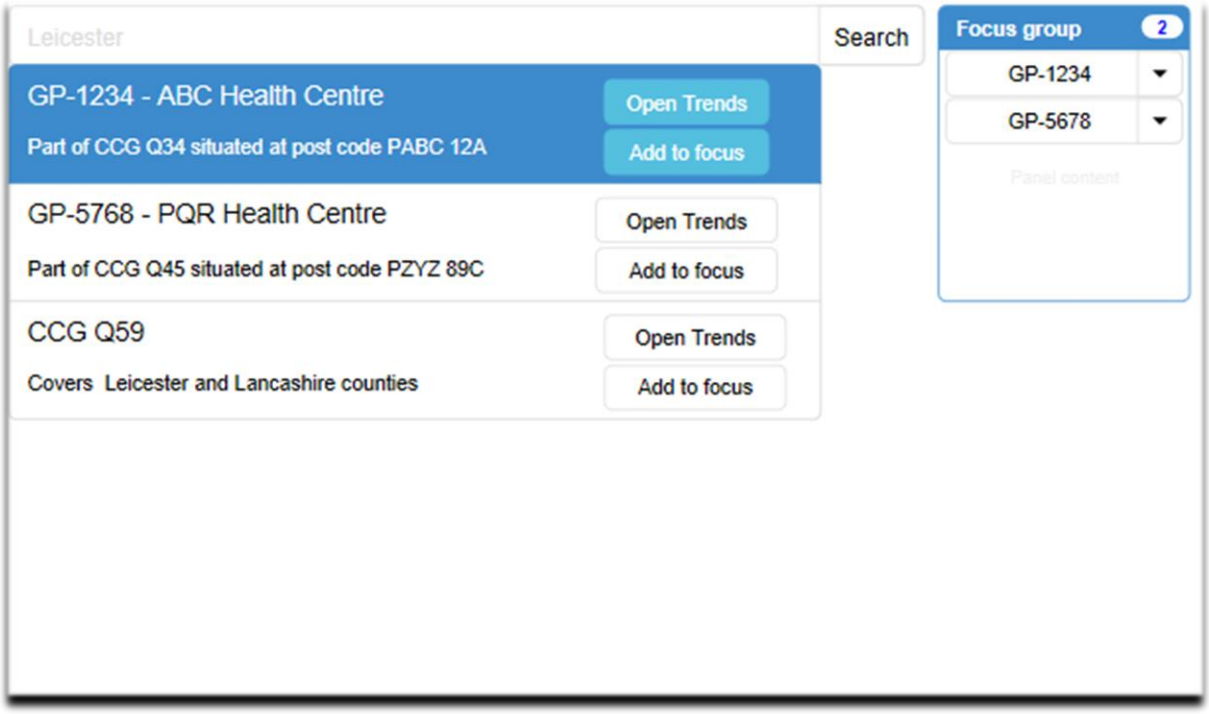


Figure 14 : Mock for search, results and focus group

The screen below shows the information shown on the items selected in the focus group. The details are general information, patient profile, practice profile and other indicators of interest.

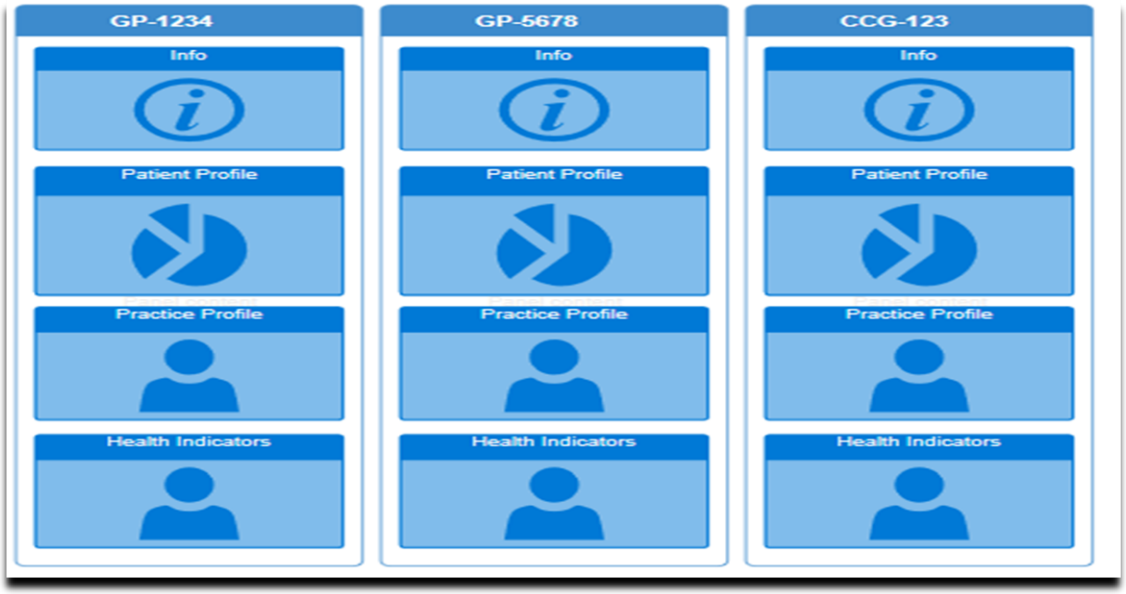


Figure 15: Mock to view the items selected in focus group

The screen below shows the specific page of GP or an item in a focus group. It provides monthly information for each chapter costs and provides a filter for a drug group.

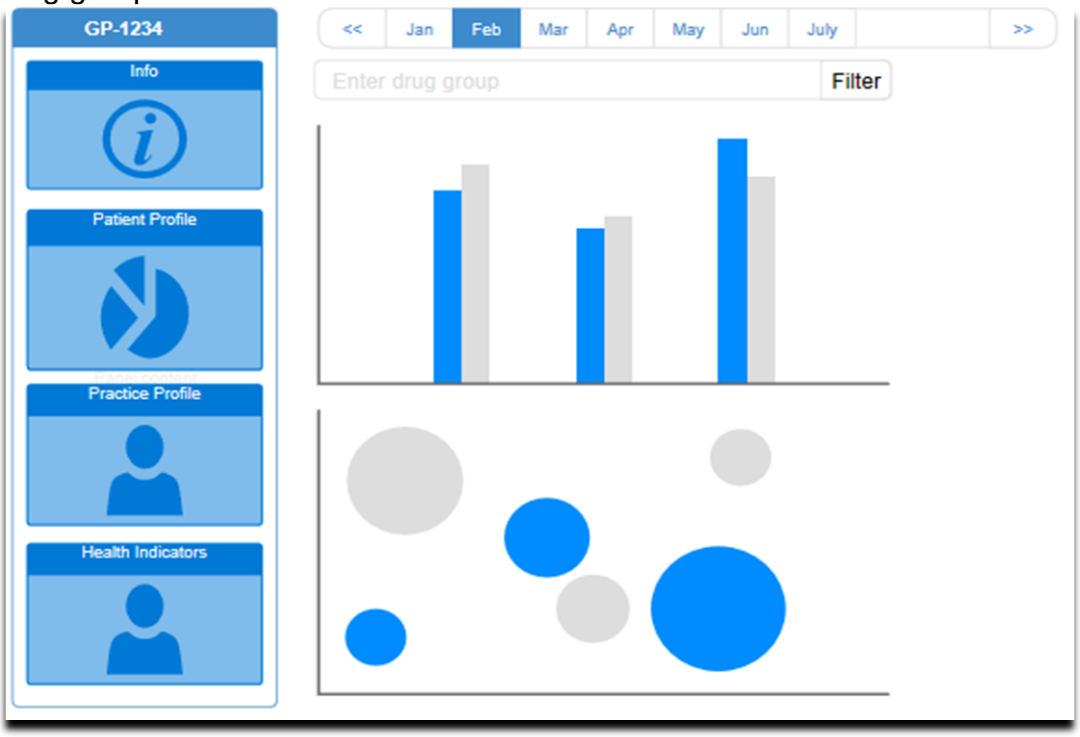


Figure 16: Specific page mock for an individual item such as GP or CCG

The screen below is used to view the clusters generated as part of the project. It provides an overview of the hovered item. The data can be filtered based on a cluster or a specific filter.

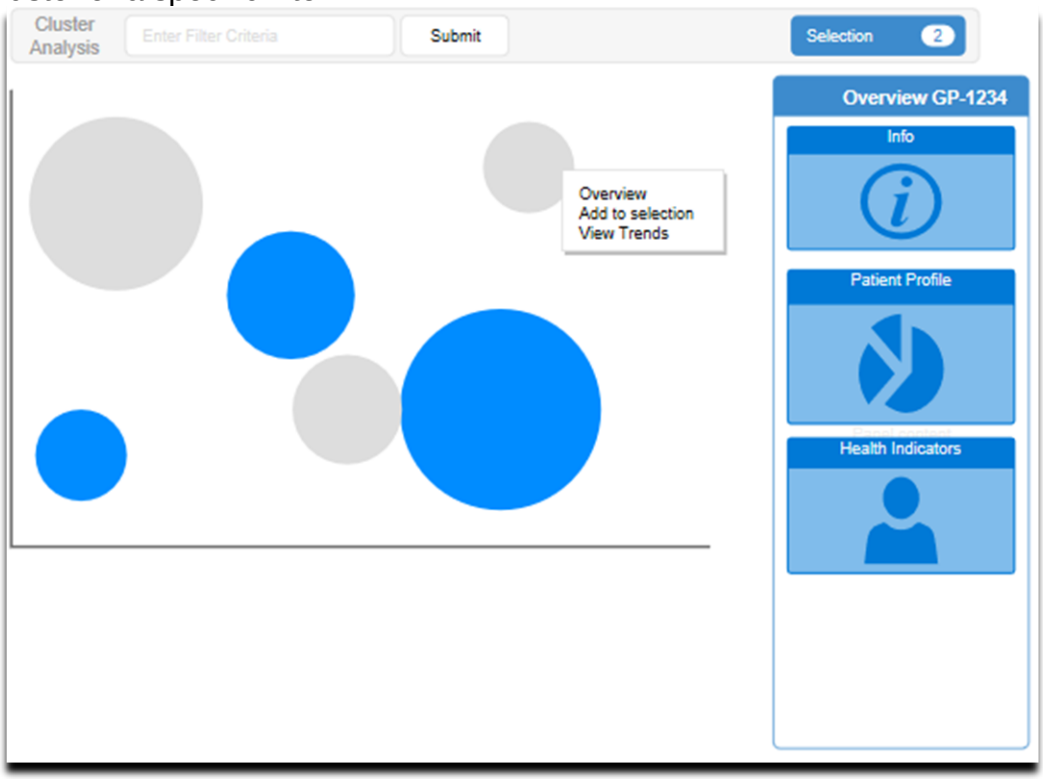


Figure 17: Cluster Analysis mock with overview for hovered item

Prototypes

<Actual screens to be updated after the demo>

Feedback

<Feedback to be updated after the demo>

Final Prototype

<Actual screens to be updated after the demo>

Conclusion

Project

< to be updated after the demo>

Challenges

- The data domain considered for the project is new for the author. Hence it was relatively difficult for the author to judge the results and needed guidance from domain expert.
- Application of data science principles on multivariate data in some instances was difficult, since the number of features was quite high.
- Understanding of the BNF or medical formulations is crucial to understand generic and branded drugs. This was taken up later in the project.
- Usage of Visualization library has a steeper learning curve than anticipated.
- The discussion on the application prototype and feedback was necessary. This was initiated very late in the project and should have planned earlier.

Future Developments

Considering the challenges faced and the understanding of the prescription data and other datasets is a new initiative. It is vital to capitalize on the domain knowledge built and work on next steps.

Following steps are proposed:
- To complete the data model for prescription cost prediction
- To conduct user interactions with different stakeholders and understand the need to advanced visualizations.
- Work on the feedback provided by the end-users during the demo. This should be developed in an iterative way with continuous involvement from the teams and stakeholders.
- To build the architecture of the system, so that it can be incorporated into other NHS platforms or OpenPrescribing.net from EDM Data labs
- In terms of visualization, it will be interesting to generate animated trends in timeline for a group of GP or CCGs in terms of:
    - Average Age Profile
    - % of Diabetic Patients or any specific disease
    - Prescription Cost
    - Patient List Total Size
    - Usage of specific medicine vs another

- Viagra Usage

- In terms of new datasets, below datasets should be explored:
  - Prescription cost analysis
  - Dispensing data (Pharmacies data) link it to prescriptions and practices.
  - ONS data – to link it to outcomes such as mortality rate and other parameters.
  - Various health indicators provided by Public Health England
  - GP survey data from the questionnaires answered by Patients

Glossary

GP	General Medical Practice
CCG	Clinical Commissioning Group
NHS	National Health Service
NHS BSA	National Health Service Business Service Authority
PHE	Public Health England
BNF	British National Formulary
IMD	Index of Multiple Deprivation
NIC	Net Ingredient Cost
ACT	Actual Cost

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