CSC8633_Group_6_Report

March 24, 2023

STRUCTURED ABSTRACT

Context

HC-One currently scours through thousands of applications every week for care home workers and nurses. However, this activity requires the recruitment team to manually evaluate the likelihood of each candidate being a successful hire or not. This process is very tedious and time consuming and may result in the loss of quality candidates.

Objectives

The main objective of this investigation is to evaluate whether each candidate would be a successful hire or not using the CRISP-DM framework. This would simplify the recruitment process and reduce the time and resources required to review each applicant.

Method

To achieve this goal, exploratory data analysis and different modelling techniques were carried out on a large dataset with information about the successful candidates and their characteristics to get answers to a set of critical questions regarding the likeliness of a candidate being selected for the role.

Results

The findings of the analysis suggest that the length of service in months is an important factor in determining the likelihood of a candidate being a successful hire. Furthermore, based on multiple modelling techniques carried out on the dataset it can be concluded that the higher the predicted length of service in months, the higher the likelihood of the candidate being successful.

Novelty

This project is done entirely using the CRISP-DM cycle methodology and focuses on creating an EDA and modelling on the dataset in which, the results of this project serve as a foundation for future projects using the CandidateSchools and EmploymentHistory datasets which could help provide more insights on the likelihood of the applicant being a successful candidate.

CRISP-DM Cycle: Scoring System to Evaluate Likelihood of a Candidate Being a Successful Hire

1 BUSINESS UNDERSTANDING

1.1 Background

In today's day and age, data can be used to simplify almost all processes with the help of tools and technologies like exploratory data analysis, predictive modelling, etc. For this project, recruitment data has been produced by the organisation HC-One. HC-One is the largest care home operator in the UK.

HC-One currently combs through 2,500 to 3,000 applications per week for care workers and nurses. However, this activity consists of a majority of noise and the recruitment team is forced to manually evaluate the likelihood of each candidate being a successful hire or not. This process is very tedious and time consuming and results in the loss of quality candidates.

Therefore, HC-One has approached the students of Newcastle University to tackle this issue by coming up with a scoring system to simplify this process.

1.2 Business Objectives

Evaluating whether each candidate would be a successful hire or not would be the main objective for this CRISP-DM cycle.

By doing this, it would simplify the recruitment process and reduce the time taken to review each applicant. Therefore, this would allow the recruitment team to recruit the highest quality of candidates.

Here, success would be defined as a high accuracy of the scoring system to predict the likelihood of a candidate being a successful hire.

1.3 Data Mining Goals (Technical Questions)

Based on the business objectives, looking for any relationship in the number of enrolments over time. This means the results could be an increase in the enrolments over time, a drop in the enrolments over time or no relationship between the enrolments and time. The next step could be to look into the relations between the demographics, number of enrolments and the periods the course has been running. The demographic to be looked into could be the country as it could provide useful insights based on the well performing industries in the specific countries.

Considering the business objective defined in chapter 1.1, the business objective could be broken down into multiple data mining goals, which are as follows:

- Selecting the necessary variables that would be required for further evaluation.
- Implementing various prediction modelling methods to predict the score to specify the likelihood of a candidate being a successful hire.
- Evaluating the various predictive modelling methods to find the best method for the data provided.

These steps provide a technical outline of the requirements for this cycle.

1.4 Project Plan

To follow the CRISP-DM cycle to achieve the business objective, the data would first need to be understood. This would mean understanding and analysing all the data to find the relevant variables useful for this particular cycle. The data would need to be prepared as required for the modelling, which generally includes cleaning, creating additional variables from the existing variables and formatting the data based on the requirements. The next step would be to carry out the required modelling process to create and solve the data mining goals. The results of the modelling stage would then be compared to the business objective to check whether it has been answered. The final step would be to generate a report and pass it on to the relevant people.

1.5 Choices of Research Tools, Models and Software Considerations

The tools used for this project are jupyter notebooks, powerbi for visualisation, python libraries like pandas, numpy, matplotlib, sklearn and cookiecutter with the data science template.

2 DATA UNDERSTANDING

For this project, the CandidateApplicationsData dataset is the only dataset being used.

2.1 Describing Data

At first glance, the CandidateApplicationsData dataset is observed to have 24,483 records and 129 different variables as observed in Table 1. This shows that the dataset is highly dimensional and feature selection will need to be carried out to retain the highly correlated and relevant features.

Number of Records	Number of Columns
24483	129

Table 1 : Number of Records and Columns in the CandidateApplicationsData Dataset

There CandidateApplicationsData dataset has NA values which will need to be cleaned. The Contracted hours column has 4 NA values, Applied Through (Channel Type) has 9,426 NA values, Applied Through (Channel) has 12,984 NA values, Home Code has 68 NA values, Advertised Salary has 693 NA values and Distance Candidate is from Job location (KM) has 5 NA values. Group Code, Type Code and Category Code columns have 127 NA values, and Competitor Data columns have 105 NA values. In addition to this, many columns have ‘Not Found’ values that can be considered as NA values. The Academic Qualifications - Count columns have 20,997 ‘Not Found’ values. The CandidateApplicationsData also has 4 duplicates as observed in Table 2.

Number of Duplicates
4

Table 2 : Number of Duplicates in the Dataset

From Table 3, it is observed that there are 3 job titles in the dataset, which are carer, nursing and senior carer. Carer consists of 19,836 records; nursing consists of 3,129 records and senior carer consists of 1,518 records. Carer makes up over 80% of the data and therefore can be concluded that the dataset is very imbalanced for each job title. This could have an impact when it comes to training the model.

```
|              |   Job Title |
|:-------------|------------:|
| Carer        |       19836 |
| Nursing      |        3129 |
| Senior Carer |        1518 |
```

Table 3 : Number of Records for each Job Title

2.2 Exploratory Data Analysis

Table 4 shows that the value of kurtosis is 39.18. When compared to a normal distribution, a big kurtosis value indicates that the distribution has a steep peak and heavy tails. The skewness value is 4.16, This indicates that the data is skewed to the right as the skewness score is positive and therefore signifies that the tail of the distribution is longer to the right. This indicates that the presence of outliers is dragging the mean to the right of the distribution.

```
|   Kurtosis |   Skewness |
|-----------:|-----------:|
|      39.18 |       4.16 |
```

Table 4 : Kurtosis and Skewness of the distribution

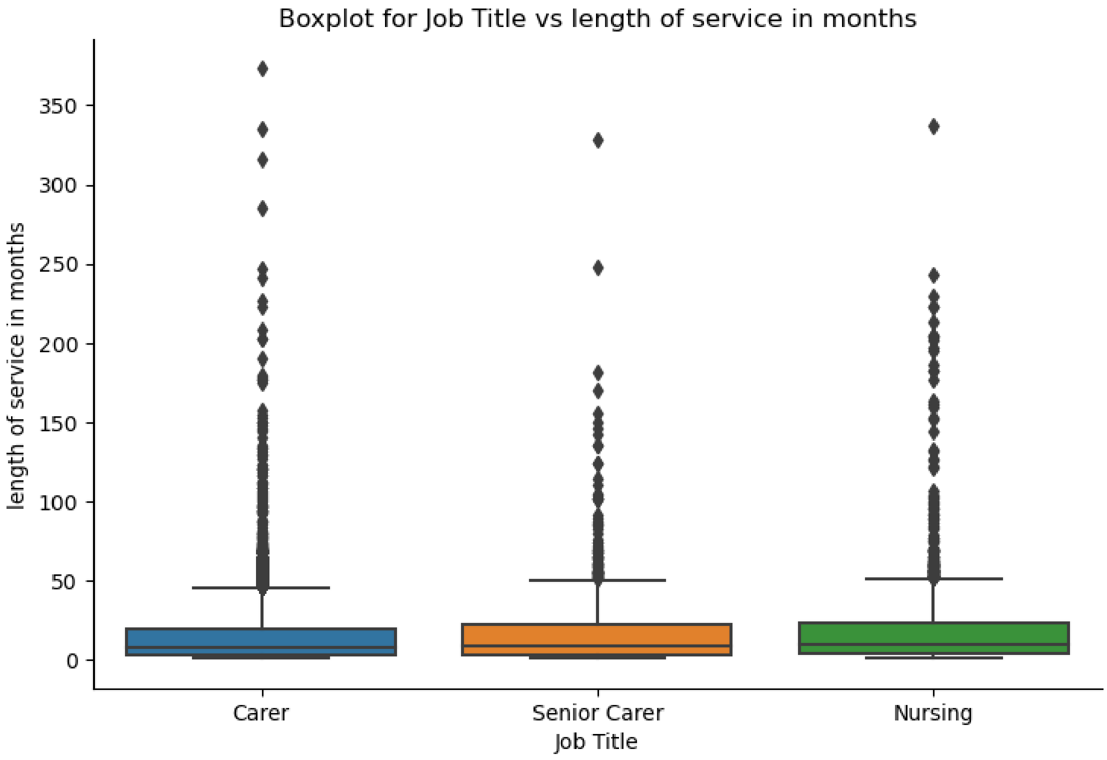


Figure 1 : Boxplot for Job Title vs Length of Service in Months

From Figure 1, it is observed that the minimum, interquartile range, median, and maximum for the job titles in the CandidateApplicationsData are very similar when compared to the length of service in months. It can also be observed that the job titles have a very high number of outliers, with carers having the most, followed by nursing and lastly senior carer. This could be because some of the candidates have a very high length of service in months which upon clarification indicates that these candidates are current employees at HC-One and have applied for a change of roles.

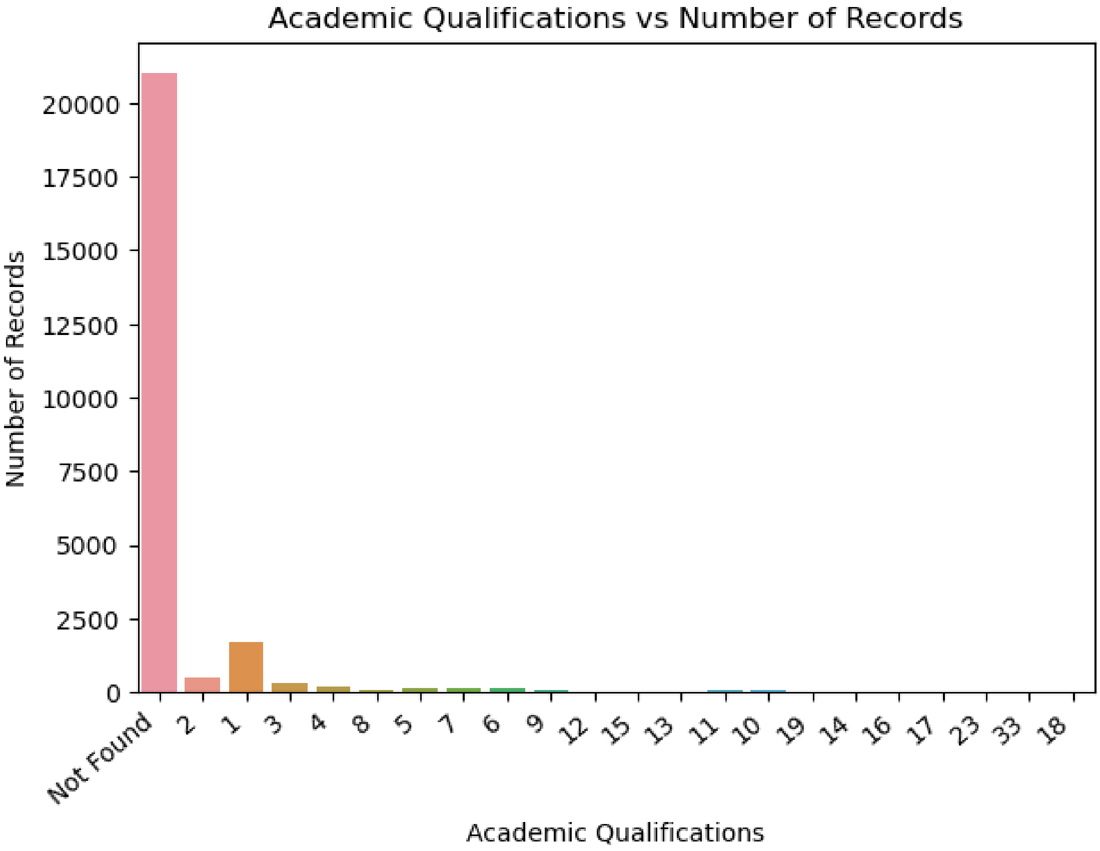


Figure 2 : Total Number of Skills vs Number of Records

From Figure 2, it is evident that there are over 20,000 records in the Total Number of Skills with NA values. This is a problem since the majority of the data from columns is not available. This would mean that this column may need to be dropped since removing the records with NA values will result in having a very low number of columns which would not be desirable.

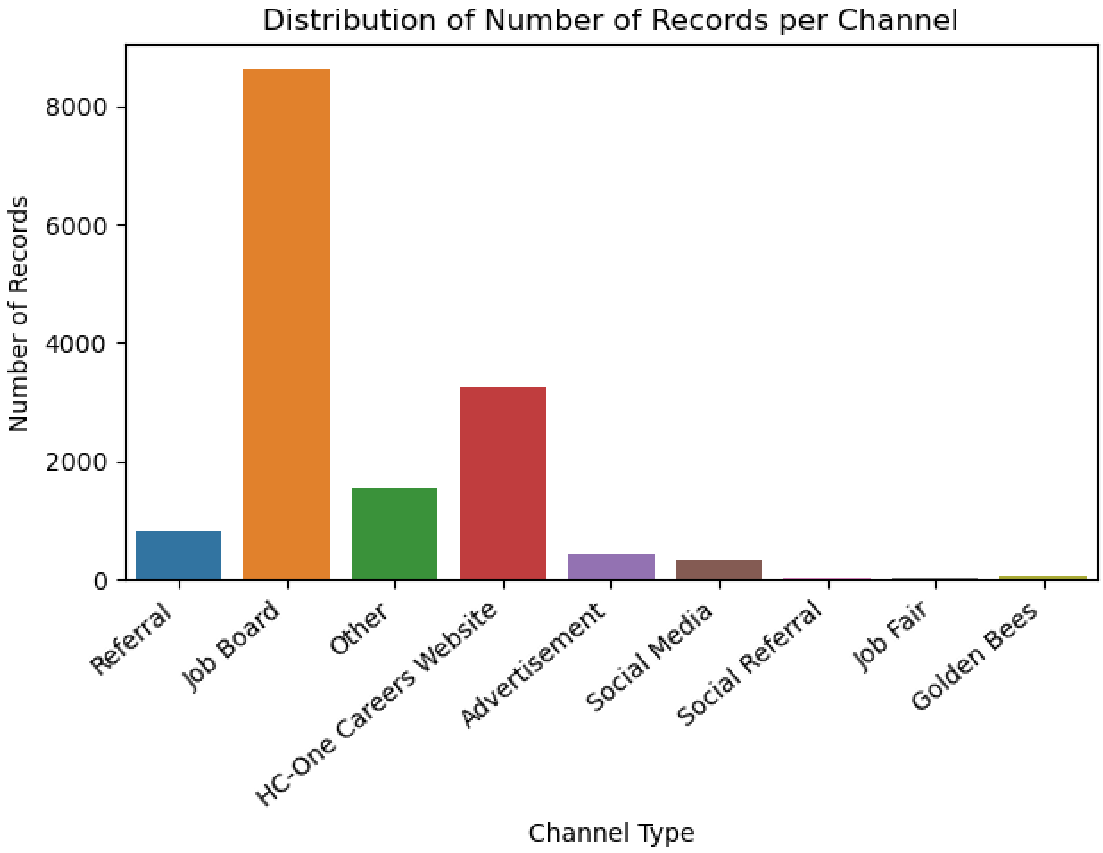


Figure 3 : Distribution of Number of Records per Channel

From Figure 3, it is observed that over 8,000 candidates applied for vacancies through the Job Board channel followed by HC-One Website, where just under 4,000 candidates applied for vacancies. These 2 channels make up for the majority of the applications. This indicates that majority of the applicants apply for vacancies posted on these two channels.

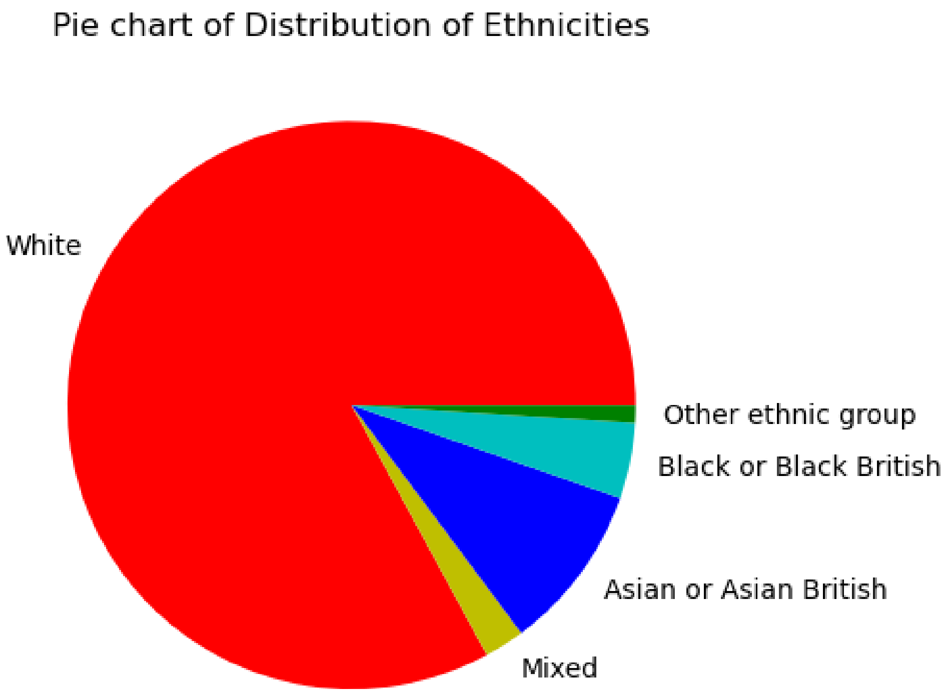


Figure 4 : Pie chart of Distribution of Ethnicities

From Figure 4, it is observed that the majority of the candidates are from catchments with a white neighbourhood, followed by Asian or Asian British, Black or Black British and so on. This could be a factor of the location since the majority of the population is white based on geography. Therefore, this introduces a significant bias in the data and when it comes to the modelling stage as it may influence the model to favour candidates from white neighbourhoods which is not accurate and falls to a lack of data for the other ethnicities. This also plays a part in data ethics. Therefore, it would be beneficial to drop these columns from the dataset in the pre-processing stage.

2.3 Data Quality Report

After exploring the provided dataset, it can be concluded that the quality of the dataset is rather poor. some of the columns have a very large number of candidates, there are duplicates of candidates for each vacancy id with a differing length of service in months and contracted hours. There are also a large number of outliers which introduces a significant amount of noise to the dataset. The advertised salary column contains a lot of different formats and requires significant time and effort to clean. All of these issues can have a significant impact when it comes to modelling and hence would need to be rectified before proceeding any further.

3 DATA PREPARATION

As discussed in the previous chapter, there is a large amount of pre-processing that is required. The various steps involved in the preparation of the data are discussed in this chapter.

3.1 Cleaning Data

The first step would be to change the ‘Not Found’ values to NA values. The next step would be to remove the duplicates that exist. The next step would be to remove all the NA values or zero values from the Contracted hours, Distance Candidate is from Job location (KM), Home Code, Advertised Salary, Group Code and Count of Care homes within 15 min drive columns. To remove the duplicate records that consist of different length of service in months and Contracted hours, all the columns except length of service in months and contracted hours are grouped and these two columns are aggregated. The length of service in months and Contracted hours are aggregated by taking the average and maximum of these columns respectively. The average length of service in months is taken since the average value would provide the most accurate representation of these candidates based on the limited information provided. Whereas, the maximum of the Contracted hours column is taken on the assumption that the maximum number of Contacted hours would provide the most accurate representation of these candidates based on the limited information provided.

3.2 Constructing Data

Here, the first step would be to convert the two time series columns, Vacancy Creation Date and Application Date to a date time format which is required for the next step. A new variable is created containing the date 2023-03-08 (the date the dataset was provided by HC-One). This is used to create a new column called month_diff where the difference between 2023-03-08 and the application date. This new column month_diff is compared to the length of services in months to identify the candidates that are current employees and applying for a new role within HC-One. This result is computed in a new column called ‘Candidate previous employee [1 = yes, 0 = no]’. If the month_diff is greater than the application date then the candidate is considered to be an existing employee and the value 1 is considered, if the month_diff is less than the application date then the candidate is considered as a new applicant with a value 0.

Cleaning the Advertised Salary columns was also necessary as they had different formats of salaries. First the “,” was removed and the re.search function was used to extract the number from the column. The first number was passed through an if loop, if the value was in the hourly wage format, the value was directly appended into a new column called ‘salary’. If the value was in the daily, monthly or annual salary, the format was changed to the hourly format and appended to the salary column.

The columns vacancy id, vacancy application id, candidate id, Vacancy Creation Date, Application Date, Application Day of Week, Application Hour in Day, Applied Through (Channel), Home Code, Advertised Salary, All, All.1, Total Skills on CV, Total, Social Demographic Code, Group, Type, Category, month_diff, mean_Contracted_hours and max_length_of_service_in_months were dropped as these columns were generally redundant and were not required as they contained data that was unnecessary for the modelling or represented an aggregation (total) of other columns.

The columns Employee: full-time, Employee: part-time, Self-employed, Unemployed (economically active), ’Full-time student (economically active), Retired, Student (economically inactive), Looking after home or family, Long-term sick or disabled and Other inactive were dropped as these values had a low correlation and logically would not have any impact on whether a candidate would be successful or not. It also brought up an ethical issue of whether the model would favour candidates coming from a particular financial background.

The columns Applied Through (Channel Type), GCSE, NVQ, A-Level, HND, Bachelors, Masters and Other.1 were dropped because the majority of the values in these columns were null and different rectification methods like imputing values or removing records with NA values were undesirable.

The columns Total population by ethnicity, White, White: Gypsy or Irish traveller, Mixed, Asian or Asian British, Asian: Indian, Asian: Pakistani, Asian: Bangladeshi, Asian: Chinese, Asian: other, Black or Black British, Black: African, Black: Caribbean, Black: other, Other ethnic group and Total population aged 16 to 74 were dropped as these columns were part of the catchment ethnicity data which introduced a bias and ethical concerns as explained in the exploratory data analysis chapter. Similarly, the columns Total Population, Males and Females columns were dropped as these columns would not be significant indicators of a candidates success and also introduced ethical concerns.

3.3 Format Data

Some of the datatypes in the columns of the dataset were still incorrect and had to be changed to numerical formats for subset selection and modelling. The length of service in months, Group Code and Competitor Data columns were converted to integer datatypes. The Contracted hours and Distance Candidate is from Job location columns and were converted to float datatypes. Finally, the Job Title and Type Code columns were encoded ordinally.

3.4 Subset Selection

For feature selection, the SelectKBest method was used to find the columns with the highest correlation. The dataset was split into two parts and stored in X and y, X contained the all columns except for the target variable (length of service in months) and y contained only the target variable column (length of service in months). Using this method, the correlation for the columns in X were determined when compared to the target variable. The top 38 features were selected as these features produced the features which consisted of variables with correlation values greater than 0.15. Principle Component Analysis (PCA) was also used for X to try and reduce the number of dimensions in the data, this produced 11 PCAs. However, this method was later scrapped as it had a significant effect on the accuracy of the models.

4 MODELLING

The modelling technique used here is a supervised learning approach. Both regression models and classification models have been implemented.

For the regression modelling, a Random Forrest regression model and a neural network model were used to predict the length of service in months. These models were not satisfactory as the best r2 scores obtained were 0.44 for the random forest regression model and 0.41 for the neural network.

For the classification modelling, a Gradient Boosting Classifier was used to predict the job title. Hyperparameter tuning was also implemented using GridSearchCV, the best hyperparameters produced can be found in Table 5. The Gradient Boosting Classifier model with these hyperparameters produced a test accuracy of 95%.

Hyper Parameters	Values
criterion	friedman_mse
max_depth	3
min_impurity_decrease	0.0
min_samples_leaf	1
n_estimators	200

Table 5 : GradientBoostingClassifier Hyper Parameters with Target Variable as the Job Title

The next classification approach was to predict the length of service in months. The dataset was split into three different datasets for each Job Title column. First, the length of service in months column was converted from a discrete variable to a categorical variable, the key for this can be found in Table 6. Next, a Random Forest Classifier was trained on each dataset using length of service in months as the target variable. RandomOverSampler was used to oversample the classes with very low frequencies in the target variable to balance the distribution for each class. SelectKBest was used to select the 10 best features based on their scores. Hyperparameter tuning was also implemented using RandomSearchCV, the best hyperparameters produced can be found in Table 7. The Random Forest Classifier model for Carer, Senior Carer and Nursing produced test accuracies of 89.99%, 87.80% and 89.25% respectively.

Interval	Count
0.628 - 013.0	11404
013.0 - 025.0	2902
025.0 - 037.0	1547
037.0 - 049.0	835
049.0 - 061.0	582
061.0 - 073.0	206
073.0 - 085.0	22
085.0 - 097.0	16
097.0 - 109.0	14
109.0 - 121.0	8
121.0 - 133.0	6
133.0 - 145.0	4
145.0 - 157.0	7
157.0 - 169.0	2
169.0 - 181.0	3
181.0 - 193.0	3
193.0 - 205.0	2
205.0 - 217.0	2
217.0 - 229.0	1
241.0 - 253.0	1
313.0 - 325.0	3

325.0 - 337.0	2
361.0 - 373.0	1

Table 6 : Length of Service in Months Converted to Labels with Frequency

Model	n_estimators	hmax_features	max_depth
Carer Model	20	sqrt	12
Senior Carer Model	5	sqrt	8
Nursing Model	5	sqrt	10

Table 7 : Random Forest Classifier Hyper Parameters with the Length of Service in Months as Target Variable for Different Models Based on Job Title

The final classification approach was to predict the length of service in months. First, the length of service in months column was converted from a discrete variable to a categorical variable, the key for this can be found in Table 8. Next, a Bagging Classifier was trained on the training data and length of service in months as the target variable. Hyperparameter tuning was also implemented using GridSearchCV, the best hyperparameters produced can be found in Table 9. The Bagging Classifier model produced a test accuracy of 92%.

Intervals	Class	Number of Samples
0-2	0	3687
2-4	1	2531
4-6	2	1729
6-8	3	1274
8-10	4	1007
10-12	5	833
12-14	6	661
14-16	7	588
16-18	8	525
18-20	9	451
20-22	10	440
22-24	11	406
24-26	12	308
26-28	13	313
28-30	14	273
30-32	15	228
32-1000	16	2319

Table 8 : Length of Service in Months Converted to Labels with Frequency

Hyper Parameters	Values
max_features	10
n_estimators	100
random_state	0

Table 9 : Bagging Classifier Hyper Parameters with Length of Service in Months as Target Variable

5 EVALUATION

The first classification model implementation predicts the Job Titles of the candidates. The classification report can be found in Table 10. The precision, recall and f1 score were excellent for the carer and nursing job titles. However, the recall and f1 score were poor for the senior carer job title but the precision remains good. This could be due to a large number of variations in the data in the senior carer job title. The model still maintains a test accuracy of 95%. This model implementation is still considered to be sub-optimal as the model predicts job titles but the length of service is not being predicted here which is assumed to be the main factor when it comes to measuring the success of a candidate.

Job Title	Precision	Recall	F1-Score	Support
Carer	0.95	0.99	0.97	2897
Senior Carer	0.84	0.49	0.62	242
Nursing	1	0.96	0.98	376
Accuracy			0.95	3515
Macro-Average	0.93	0.81	0.86	3515
Weighted Average	0.95	0.95	0.95	3515

Table 10 : Classification Report for Model with Job Title as Target Variable

The second classification model implementation predicts the length of service in months of the candidates after separating the dataset into 3 by job title. The classification reports for each dataset can be found in Tables 11, 12 and 13. The precision, recall and f1 scores were excellent apart from the classes from 0 to 4, these classes are considered to be poor. These models also maintain test accuracies of 89.99%, 87.80% and 89.25% respectively. However, this model implementation is still considered to be sub-optimal as the approach is not scalable if the number of different job titles increases to a large number.

	precision	recall	f1-score	support
0	0.84	0.4	0.54	1898
1	0.6	0.55	0.58	1863
2	0.68	0.58	0.63	1874
3	0.69	0.74	0.71	1835
4	0.62	0.87	0.72	1869

5	0.85	0.95	0.89	1851
6	0.9	1.0	0.95	1888
7	0.98	1.0	0.99	1962
8	0.97	1.0	0.99	1953
9	1.0	1.0	1.0	1857
10	1.0	1.0	1.0	1832
11	0.99	1.0	1.0	1866
12	1.0	1.0	1.0	1923
14	1.0	1.0	1.0	1859
17	1.0	1.0	1.0	1824
18	1.0	1.0	1.0	1886
19	1.0	1.0	1.0	1928
20	1.0	1.0	1.0	1944
22	1.0	1.0	1.0	1888
Accuracy			0.9	35800
Macro Average	0.9	0.9	0.89	35800
Weighted Average	0.9	0.9	0.9	35800

Table 11 : Classification Report for Model with Length of Service in Months as Target Variable for Carer Job Title

	Precision	Recall	F1-score	Support
0	0.84	0.4	0.54	1898
1	0.6	0.55	0.58	1863
2	0.68	0.58	0.63	1874
3	0.69	0.74	0.71	1835
4	0.62	0.87	0.72	1869
5	0.85	0.95	0.89	1851
6	0.9	1.0	0.95	1888
7	0.98	1.0	0.99	1962
8	0.97	1.0	0.99	1953
9	1.0	1.0	1.0	1857
10	1.0	1.0	1.0	1832
11	0.99	1.0	1.0	1866
12	1.0	1.0	1.0	1923
14	1.0	1.0	1.0	1859
17	1.0	1.0	1.0	1824
18	1.0	1.0	1.0	1886
19	1.0	1.0	1.0	1928
20	1.0	1.0	1.0	1944
22	1.0	1.0	1.0	1888
Accuracy			0.88	2196

Macro Average	0.89	0.88	0.87	2196
Weighted Average	0.89	0.88	0.87	2196

Table 12 : Classification Report for Model with Length of Service in Months as Target Variable for Senior Carer Job Title

	precision	recall	f1-score	support
0	0.41	0.61	0.49	238
1	0.65	0.46	0.54	237
2	0.64	0.54	0.59	246
3	0.81	0.63	0.71	274
4	0.87	0.8	0.83	248
5	0.93	1.0	0.96	254
6	0.91	1.0	0.95	227
7	1.0	1.0	1.0	251
8	0.95	1.0	0.98	255
9	1.0	1.0	1.0	259
10	1.0	1.0	1.0	262
12	1.0	1.0	1.0	252
13	1.0	1.0	1.0	267
15	0.98	1.0	0.99	223
16	0.95	1.0	0.97	242
17	1.0	1.0	1.0	260
19	1.0	1.0	1.0	254
21	1.0	1.0	1.0	255
Accuracy			0.89	4504
Macro Average	0.89	0.89	0.89	4504
Weighted Average	0.9	0.89	0.89	4504

Table 13 : Classification Report for Model with Length of Service in Months as Target Variable for Nursing Job Title

The final classification model implementation predicts the lenght of service in months of the candidates. The classification report can be found in Table 14. The confusion matrix plot for this model can be found in Figure 5. The precison, recall and f1 score were generally excellent except for the classes 0, 1, 2 and 16, where class 2 and 16 were still good. The model still maintains an overall test accuracy of 92%. This shows that this implementation is a balanced approach and is also scalable. The success of the candidate based on the length of service in months would be based on the requirements from HC-One. A good threshold would be a class 5 and above. However, if the requirement is for a temporary or a short term hire a lower class would be prefereble. If a long term hire is is required, a higher class would be preferable.

Class	precision	recall	f1-score	support
0	0.62	0.48	0.54	733
1	0.73	0.66	0.7	751
2	0.83	0.84	0.83	714
3	0.89	0.92	0.91	764
4	0.92	0.97	0.94	668
5	0.94	0.99	0.96	745
6	0.94	1	0.97	777
7	0.95	0.99	0.97	730
8	0.97	1	0.98	737
9	0.99	0.99	0.99	778
10	0.97	1	0.98	760
11	0.96	1	0.98	712
12	0.98	1	0.99	734
13	0.97	1	0.99	738
14	0.99	1	0.99	733
15	0.98	1	0.99	719
16	0.94	0.83	0.88	743
Accuracy			0.92	12536
Macro Average	0.92	0.92	0.92	12536
Weighted Average	0.92	0.92	0.92	12536

Table 14 : Classification Report for Model with Length of Service in Months as Target Variable

Comparing the evaluation to the data mining goals defined in chapter 1, it is evident that all the data mining goals have been appropriately met. Therefore, the business objective that was defined in chapter 1 was completed and was successful as a highly accurate model was created to indicate whether a candidate would be successful as per the requirements of the recruiters. The solution provided is also scalable and is therefore an appropriate solution for this business objective.

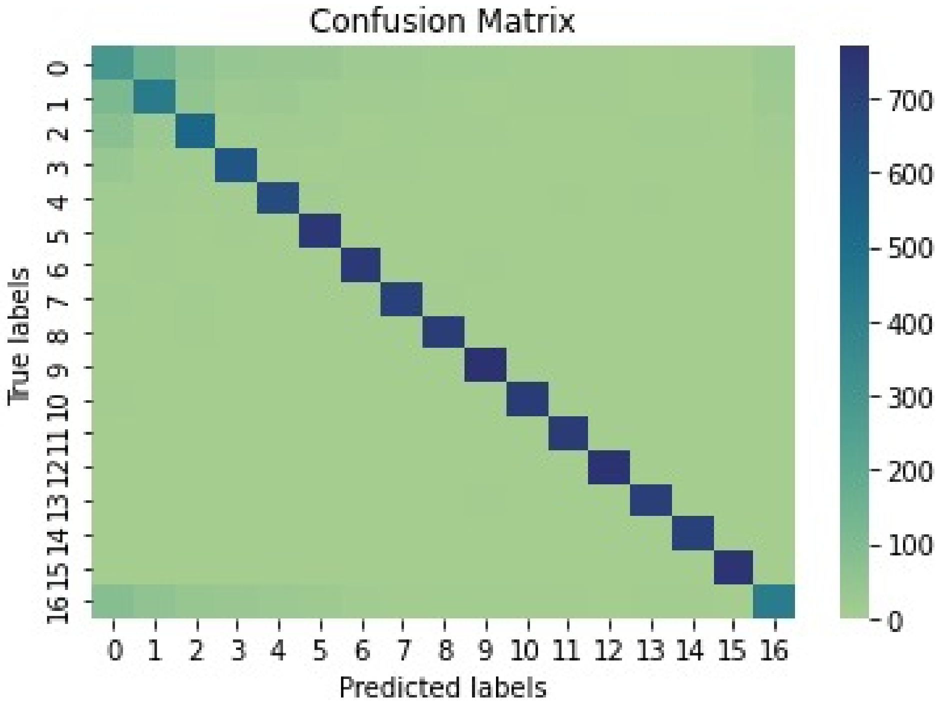
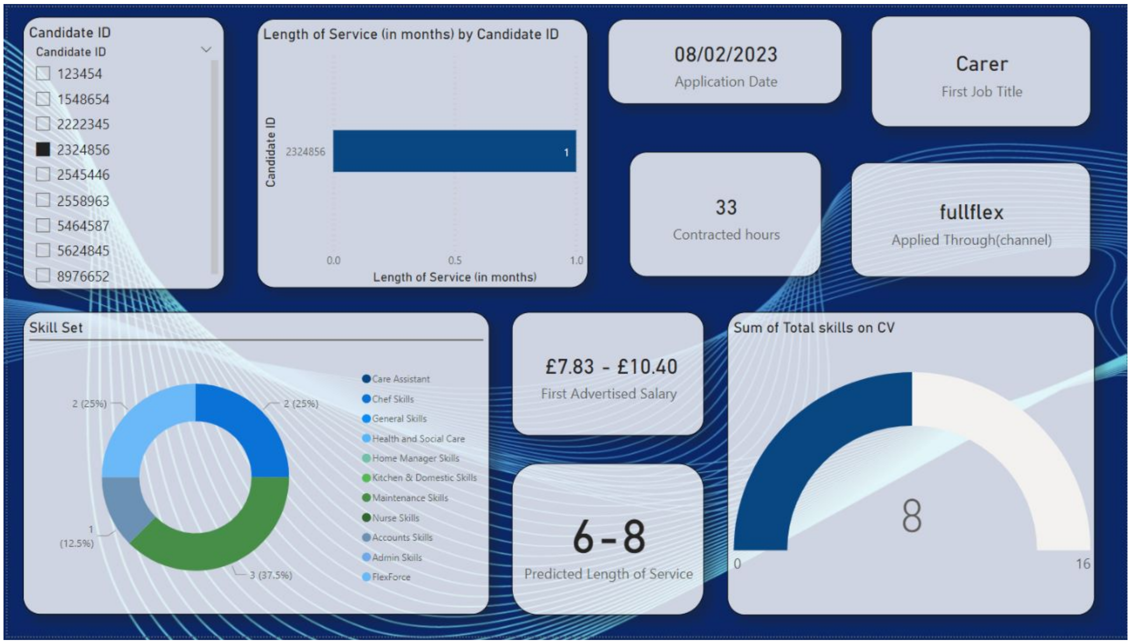


Figure 5 : Confusion Matrix Plot

6 VISUALISATION

The dashboard provides a comprehensive overview of the candidate's application data. Using the top left box, the user can search for a candidate by entering their unique 'Candidate ID'. Once the ID is entered, the dashboard displays the candidate's 'Length of Service', which reflects how long they have been working in the company. In addition, the dashboard presents the 'Channel' through which the candidate applied, along with the date of their application and the 'Job Title' they applied for. Furthermore, the dashboard features a pie chart that displays the candidate's 'Skill Set' and the total number of skills listed on their CV. This dashboard can be viewed in Figure 6.



Candidate ID

Candidate ID

□ 123454
□ 1548654
□ 2222345
■ 2324856
□ 2545446
□ 2558963
□ 5464587
□ 5624845
□ 8976652

08/02/2023
Application Date

Carer
First Job Title

33
Contracted hours

fullflex
Applied Through(channel)

£7.83 - £10.40
First Advertised Salary

6-8
Predicted Length of Service

Figure 6 : Representation of Visualisation

7 DEPLOYMENT

Since no models are being deployed, there is no deployment necessary. Therefore, the process of converting the jupyter notebook report to a pdf document is considered to be the deployment.

8 FUTURE SCOPE

To further develop this work, using the probabilities to create a scoring system that could indicate the likelihood of a particular candidate is a successful hire along with the predicted length of service in months for that specific candidate. Using a logarithmic scale for this would be ideal since the range of values is very large.

Implementing a Natural Language Processing model (NLP) to pick up keywords from the applicant's CV and using these keywords to predict whether a candidate would be suitable for particular job titles. This can be added to the existing classification model which predicts the length of service for each candidate.

Joining the CandidateSchools and EmploymentHistory datasets with the CandidateApplications-Data dataset could help provide more insights for the applicants. This new learning could be implemented to determine whether a candidate would be successful.

9 CONCLUSION

In conclusion, the datasets provided by HC-One were analysed and meaningful insights were gained based on the candidate applications data. These insights were used to understand what approaches could be taken to tackle the business objectives. After analysing the dataset, it was found that length of service in months was a significant factor in determining the likelihood of a candidate being successful. Using the data provided, the necessary pre-processing steps were executed and the feature selection was implemented to select the features having the highest correlation. With the pre-processed data, regression and classification models were trained and the results were noted. The model classifying the length of service in months for all the job titles performed the best. This model was also the most scalable. The desirable candidates were the candidates with a higher predicted length of service in months. This indicates that these candidates have higher likelihood of being successful hires.