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**Assessment Cover Page**

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| **Module Title:** | *Programming for Data Analytics*  *Statistics for Data Analytics*  *Machine Learning for Data Analysis*  *Data Preparation & Visualisation* |
| **Assessment Title:** | *Exploring the Link Between Population Trends and Crime Rates in Ireland* |
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| **Assessment Due Date:** | *5th Jan 2024* |
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**Declaration**

|  |
| --- |
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**Analysing Transportation System in Ireland, Focused on Bike Sharing in Dublin and Comparing to equivalent service in Barcelona - Spain.**

# Abstract

*This project is available on github:*

*link:* https://github.com/jmdtanalyst/MSC\_DA\_CA2\_Transport\_Ireland

***KEYWORDS:*** *population growth, crime rates, Ireland, crime prevention, policy*

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# Introduction

DUBLIN

As of today, December 5, 2023, there are three bikeshare services operating in Dublin:

Dublinbikes: This is the oldest and most well-established bikeshare service in Dublin, having been launched in 2009. It is operated by TFI Cycles, a subsidiary of the National Transport Authority (NTA). Dublinbikes has over 3,500 bikes and 450 docking stations located throughout the city center and inner suburbs.

Bleeper: This is a stationless bikeshare service that was launched in Dublin in 2018. It is operated by Bleeper Bike, a private company. Bleeper bikes can be unlocked and locked using a smartphone app. There are currently over 800 Bleeper bikes available in Dublin.

Moby: This is an electric bikeshare service that was launched in Dublin in 2023. It is operated by Moby Bikes, a private company. Moby bikes can be unlocked and locked using a smartphone app. There are currently over 300 Moby bikes available in Dublin.

All three bikeshare services are convenient and affordable ways to get around Dublin. Dublinbikes is the most extensive service, with the largest number of bikes and docking stations. Bleeper is a good option for shorter trips, as there are no docking stations to worry about. Moby is a good option for longer trips or for those who want the assistance of an electric bike.

BARCELONA

Bicing is the older of the two services, having been launched in 2007. It is operated by Clear Channel and has over 6,000 bikes and 400 docking stations. Bicing is a public service and is intended for short-term journeys of up to 30 minutes.

AMBici is a newer service that was launched in 2023. It is operated by Transports Metropolitans de Barcelona (TMB) and has over 2,600 bikes and 236 docking stations. AMBici is an electric bike-sharing service and is also intended for short-term journeys of up to 30 minutes.

Both Bicing and AMbici are convenient and affordable ways to get around Barcelona. However, there are some key differences between the two services. Bicing is a more established service with a wider network of docking stations. AMbici is a newer service with a smaller network of docking stations, but it offers electric bikes.

Ultimately, the best bike-sharing service for you will depend on your individual needs. If you are looking for a convenient and affordable way to get around Barcelona for short-term journeys, then either Bicing or AMbici would be a good option.

# Data Preparation and Visualization

## 1.1 Data Wrangling

Data Wrangling is the first step to be performed with the data. This process consists of cleaning, transforming, and manipulating the data to make it more usable for analysis. This process will be performed in a Jupyter Notebook:

* File name: MSC\_DA\_CA1\_Jose\_Mario.ipynb
* Process: 'Phase 01 - Data Wrangling'

The project will use three datasets:

* CJQ01-recorded\_crime\_2002-2022.csv
* PEA04-Estimated\_Population-2011-2023.csv
* PEA07-Estimated\_Population-1996-2017.csv

It will be necessary to clean the data, organize, and rename some columns, as well as merge the datasets.

During the cleaning process, on “crime\_df” dataframe, one ‘NaN’ value was found in one row, filling it with the mean wouldn't be a suitable approach. Using the mean would distort the statistics because the mean would consider the other types of offenses in its calculations. The best approach is to drop the row, ensuring that the dataset contains only complete and reliable information.

The method .dropna() has been used in this dataframe.

## 1.2 Exploratory Data Analysis (EDA) Method and Insights

EDA allows us to gain an overall understanding of the dataframes, detect relationships between variables, and examine the distribution of the variables of interest. In this study, the exploratory data analysis (EDA) step will be used to perform both statistical analysis and visualization tasks.

The preferred approach is multivariate analysis, which explores the relationships between three or more variables. Specifically, I will examine the relationship between population and crime rates.

I chose these methods because they will enable me to gain insights into the overall trends in population, as well as the overall situation of the crime rate and its relation to population trends.

After the first process, “Data Wrangling”, the population\_df and crime\_df datasets are shown below:"

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A screenshot of a graph

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## 1.2.1 Performing the EDA:

This process will be performed on Jupyter notebook: **MSC\_DA\_CA1\_Jose\_Mario.ipynb** and it was called **“**Phase 02 - EDA ”

**Skewness:**

Skewness is a measure of how much the distribution of a random variable deviates from symmetry.

It is important to consider the skewness when performing statistical tests. In some statistical tests, if the data is skewed, these tests may not be valid.

Skewness is classified as follows:

Highly skewed: Less than -1 or greater than 1

Moderately skewed: Between -1 and -0.5 or between 0.5 and 1

Approximately symmetrical: Between -0.5 and 0.5

Histograms or distplots can be used to visualize skewness. However, distplots are generally considered to be a better option because they provide more information about the shape of the data distribution.

A group of blue and white graphs

Description automatically generated*Figure 01: distplot - Skewness by region*

**Insights**

From this figure, we can observe that aside from the Border region, which exhibits a highly positive skew, the skewness of the data is relatively mild. Therefore, it is not necessary to perform any transformations on the data for the purpose of data visualization.

Below, the print of the skew value for each region:

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**BoxPlot:**

We can get some insights from the boxplot and answer a variety of questions about the data, for example: Identify the median value of the data, determine whether the data is skewed, identify outliers and compare the distributions of two or more groups of data.

A chart with different colored boxes

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*Figure 02: Boxplot - population by region*

**Insights:**

From this boxplot we can get some Insights:

The median population of the "Border" region is the highest, also the boxplot shows that there is a significant variation in population between the different regions.

The Border and West regions have the highest populations, while the South-West region has the lowest population.

It is possible to detect some outliers on the Border region, what require further investigation.

**Outliers:**

Outliers are data points that significantly differ from the majority of observations in a dataset. They can be caused by various factors, including measurement errors, data entry errors, or natural variation in the population.

To identify potential outliers, statistical methods like the Z-score or the Interquartile Range (IQR) can be employed. The Z-Score Method is particularly useful when dealing with data that follows a normal distribution. In contrast, the IQR method is robust and less sensitive to extreme values, making it well-suited for data that is skewed or non-normally distributed.

Considering that the 'Border' column in this dataset is highly skewed, the IQR method is the more appropriate choice for identifying potential outliers.

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Although the values are potential outliers, observing the histological population growth in the “Border” region, it appears to be a natural growth of the population.

**Line Chart:**

Line charts are a useful tool for detecting trends, relationships, and comparisons.

To visualize the grown of the population, a line chart has been created.

A graph of different colored lines

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*Figure 03 – Population by region over time*

**Insights:**

One of the most obvious insights is the overall growth of population over time, The chart shows the regional variation in population growth. Some regions, such as Dublin, have experienced more rapid growth than others.

Also, we can observe some anomalies in the regions "Border" and "South-East", which show a decrease in population.

Considering the trend line, and furthermore using Machine Learning, we can get insights into the future of population.

**Pie Chart:**

Pie charts are also useful for detecting trends, relationships, and comparisons, but it is important to limit the number of items in the chart to avoid creating a cluttered image.

Pie charts use a 1D array as input, so we need to convert the data variable to a 1D array using the NumPy ravel() function.

In this case, we will plot two pie charts: one with data from 2013 and one with data from 2023, so that we can observe any changes over the 10-year period.

A close-up of a pie chart

Description automatically generated*Figure 04 – Population by region 2013 and 2023*

**Insights:**

From the pie chart, we can observe that the biggest region in population Is the Dublin region, and the smallest is Midland.

Comparing both pie charts, we can see the following changes:

The Dublin region has become even more populous over the past decade, increasing its population share from 32.1% to 33.2%.

The Border region has also experienced a slight increase in population share, from 16.5% to 16.9%.

Overall, the population of Ireland is becoming more concentrated in the Dublin region. This may be due to a number of factors, such as job opportunities, educational opportunities, and cultural amenities.

## 1.2.2 Exploring Crime Rate dataset:

From the crime dataset, we can get some information.

Which Garda Station has registered more incidents, and which one has registered less incidents:

|  |  |
| --- | --- |
| **More Incidents:**  A screenshot of a phone  Description automatically generated | **Less Incidents:** |

Also, we can have an overview of the Type of Offences

A graph with text and numbers

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*Figure 05 – Overview of type of offences*

**Insights:**

From this plot, we can observe that the most prevalent offenses in Ireland are theft and related offenses, public order and other social code offenses, and damage to property and the environment. Conversely, kidnapping and related offenses are the least common type of offense.

# 2.0 Statistics for Data Analytics

We can use a set of tools and techniques for collecting, organizing, summarizing, analysing, and interpreting data.

Statistical techniques were employed in this project within the Jupyter notebook named “MSC\_DA\_CA1\_Jose\_Mario.ipynb”, encompassing both “Phase 3, which focused on statistics, and Phase 4, which centred on machine learning”.

By using the method describe, we can get important information from the result.

**Mean**: The average of crime over these types.  
**Max**: The largest value in the type of crime.  
**Median**: (middle value) of recorded crime incidents.  
**Minimum**: and maximum values in the dataset.  
**Standard deviation** :to measure the spread of the data.

Applyiing the .describe() method on crime\_df:

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From this “.describe()” method, we can get some insights:

* The average number of crimes in the dataset is 34.78.
* The standard deviation is 143.66, which means that the number of crimes varies widely.
* There are a few outliers in the dataset, with the maximum number of crimes being 6523.
* The median number of crimes is 4, which means that half of the crimes in the dataset are less than or equal to 4, and half are greater than or equal to 4.

Histograms provide a visual representation of the distribution of data, it is useful for understanding the characteristics of the data.

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*Figure 06 – histogram of crime\_df*

**Insights:**

The distribution of the VALUE column is skewed to the right. This means that there are more values on the right side of the distribution than on the left side.

The median value of the VALUE column is between 10,000 and 15,000.

## 2.1 PFM and CDF

Pmf and Cdf are classes that represent probability mass functions (PMFs) and cumulative distribution functions (CDFs), respectively.

* A PMF is a function that gives the probability of each possible value of a discrete random variable.
* A CDF is a function that gives the probability that a random variable will take on a value less than or equal to a given value.

The best approach to visualize the PMF is plotting a wide bar chart.

A graph with blue and black text

Description automatically generated *Figure 06 – pmi of Type of Offence*

To get the exact PMI values, we can also explore the PMI itself by printing the values.

The highest probability:

A computer screen shot of a computer code

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The lowest probability:

A close-up of a computer screen

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**Insights:**

Based on the PMF chart we can make the following analyses:

The most common type of offence is theft and related offences with 30%. This is followed by public order and other social code offences

The least common types of offences are kidnapping and related offences.

The distribution of offences is skewed, with a few types of offences being much more common than others.

**Exploring CDF:**

A CDF is a function that gives the probability that a random variable will take on a value less than or equal to a given value.

A graph with numbers and lines

Description automatically generated*Figure 07 – CDF of crime\_df*

**Insights from the CDF:**

The CDF chart shows that the VALUE column is skewed to the right. This means that there is a relatively small number of crimes with very high values, and a large number of crimes with lower values.

Most crimes have relatively low values.

There is a small number of crimes with very high values.

## 2.2 Crime Rate Statistics

**Evolution of top 5 type of offence from 2003 to 2022:**

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*Figure 08 –Evolution of top 5 type of Offence 2003 to 2023 Q2*

**Insights:**

The chart shows that all five types of offences have increased over time. Theft and related offences has shown the smallest increase, followed by public order and other social code offences. The other three types of offence have all shown larger increases. After 2021, all 5 types of offences started to increase, with theft and related offences leading the increase.

**Population Growth vs Crime Rate**

To compare population growth and crime rates, we will filter the population dataframe to extract total population figures between 2003 and 2022, excluding regional data. We must then multiply the population by 1000 to account for the fact that the population is shown in thousands and crimes are shown in units.

To compare the evolution of the population and crime rate, a line chart has been plotted.

A graph of a line and a line

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*Figure 09 – Line Chart comparing total crime and population growth*

**Insight**

From the figure above, we can see that the crime rate in Ireland has declined significantly over time, while the population has grown steadily.

This suggests that the crime rate in Ireland has declined even faster than the population has grown. This is a positive development.

**Correlation**

To get a better understanding of the relationship between population growth and crime rate, we can calculate the correlation coefficient between the two variables.

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*Figure 10 – Heatmap correlation coefficient population and crime*

**Insight from Correlation Heatmap**

The correlation coefficient for the population growth and crime rate dataset is --0.582652. This indicates a moderate negative correlation between the two variables. This means that as the population increases, the crime rate tends to decrease.

# 3.0 Machine Learning for Data Analysis

For the purpose of developing a machine learning model, I will utilize the new generated dataset, Pop\_and\_crime\_df.csv. To prepare the data for Machine Learning, I will standardize the crime rate providing the crime rate per 100,000 people, which is a common way to standardize crime rates for comparison.

I will use CRISP-DM project management framework, applying multiple machine learning models and examine the performance of each model.

These tasks will be performed in the jupyter notebook: MSC\_DA\_CA1\_Jose\_Mario.ipynb, Phase 4 - Machine Learning.

## 3.1 Handling Outliers and Skewness:

In the Machine Learning phase, it is crucial to address skewness, handle outliers, and standardize the data.

To identify potential outliers, statistical methods like the Z-score or the Interquartile Range (IQR) can be employed.

Considering that this dataset is highly skewed, the IQR method is the more appropriate choice for identifying potential outliers.

After applying the IQR method, we have a table with the rows with outliers:

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For skewness, as we have more columns, I've implemented a “For” loop to identify and print the skewness only when it exceeds the threshold.

**Skewness vs outliers:**

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As a result, we have 4 skewed columns, with some right skewness and others left skewness. Also, we can observe that there are 5 rows with outliers.

Considering that the dataframe contains 20 rows, removing outliers would eliminate 5 rows. In this scenario, the preferred approach is to transform the data to mitigate skewness rather than removing outliers.

For data transformation, we need to understand the skewness, for right skewness we can apply some transformation methods, whereas for left skewness, we need to apply another transformation method.

For right skewness, I’ve applied the following transformation methods:

**Square Root Transformation:**

Square root transformation is suitable for right-skewed (positively skewed) data, it has better performance in mildly right-skewed.

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After applying square root, the result was this:

As the result, them column with mild skewness was adjusted, but the columns with high skewness was not.

**Cube Root Transformation:**

Cube rooting can help reduce the influence of extreme values or outliers in the data, making the data more robust to the presence of outliers.

After the cube root transformation, the outcome was as follows: The cube root proved to be more effective than the square root in reducing skewness, but it was still not sufficient to fully adjust the highly skewed column.

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**Log Transformation:**

Log transformation is a common way to handle right-skewed data. It can be used to improve the normality of the data, which is a requirement for regression models.

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Log transformation proved to be more effective than the square root and cube root in reducing skewness, but it was still not sufficient to fully adjust the highly skewed column.

**Reciprocal Transformation:**

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Description automatically generatedReciprocal transformation is effective in reducing the impact of outliers, especially for data with right-skewness.

Even after handling the skew with reciprocal transformation, the data was reduced to zeros, which is not useful for regression.

The best approach was applying both Log transformation and Reciprocal transformation consecutively, which handled the skewness successful, and it is still suitable for regression.

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**Left Skewness:**

Now we have only the columns with negative skewness (left skew). For left skewness, we have some transformation methods:

* Square Transformation;
* Cubes Transformation;

**Square Transformation:** The square transformation is effective in reducing left skewness. It's the counterpart of the square root transformation and can be used when the data is left-skewed.

A screenshot of a computer

Description automatically generated

**Cubes Transformation:** Exponential transformations can be applied to data with negative skewness to expands small values and compresses large values, which will make the distribution more symmetric.

A screenshot of a computer

Description automatically generated

Applying square or cube transformation was effective at reducing skewness, but it was not enough to fully adjust the highly skewed columns. The best option is to apply both transformations.

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Now we have our data cleaned and more symmetric, we can apply some predictions and Machine learning models.

## 3.2 Principal Component Analysis (PCA):

As we have a dataset with 16 columns, it is a good approach to reduce the dimension, for this purpose, Principal component analysis (PCA) technique will be applied. PCA simplifies the complexity of the dataset while preserving its essential structure.

Applying PCA with 10 components to determine the optimal number of components for dimensionality reduction:

A graph with a red line

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*Figure 11 – Cumulative Explained Variance*

Based on this chart, we can assume that the best number of components is 5, because from 1 to 5 they explain over 90% of the variance in the data. After 5 components, the variance explained by each additional component drops off sharply, indicating that these components are not capturing much important information.

**Predicting Crime Rate after applying PCA.**

For predicting the crime rate, Its necessary to use Machine Learning to predict the number of crime in a given year.

As we know the features and the target of our data, we will apply supervised learning to predict the crime rate:

**Linear regression:**

Linear regression is a powerful model that can be used to predict continuous variables, such as population growth or crime rate, that is because it is used to model the relationship between a dependent variable and one or more independent variable.

For this purpose it’s the best option because the variables and the target are known.

After creating the linear regression model and applying, the residual plot can provide the accuracy of the model.

A graph with a line and dots

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*Figure 12 –Linear regression residual plot*

The residual plot shows that the residuals for linear regression model are randomly scattered around the zero line. This indicates that the model is a good fit for the data.

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**R-squared score (R^2)** is a measure of how well the model explains the variation in the data. A higher R^2 score indicates a better fit. The R^2 score on the training set is 1.000 and the R^2 score on the test set is 0.998.

**Mean squared error (MSE)**

The mean squared error (MSE) is a measure of how close the predicted values are to the actual values. It is calculated by taking the average of the squared differences between the predicted values and the actual values.

Based on the MSE and R^2 results, we can assume that the model is performing well, and can be applied in a new dataset.

**Lasso Regression:**

Appling Lasso Regression, we had also a good result, which means that this model can be applied in a new dataset:

A graph with a red line

Description automatically generated  
*Figure 13 – Lasso Regression Residual Plot*

A computer code with text

Description automatically generated with medium confidence

Similar to Linear Regression, Lasso regression also had a very good result. The training set score and test set score are both 1.00, which means that the model is perfectly fitting the data.

**Random Forest Regressor:**

To compare the performance of different models. I also applied Random Forest Regressor.

Applying the Random Forest Regressor model, this was the result:

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With a MSE very low (0.00563426) and an R-squared very high (0.99359531), this model also performs very well.

**Comparing the results:**

|  |  |  |
| --- | --- | --- |
| Linear Regression:  MSE train: 0.000, test: 0.002  R^2 train: 1.000, test: 0.997 | Lasso Regression:  Training set score: 1.00  Test set score: 1.00 | Random Forest Regressor:  MSE: 0.00563426  R-squared: 0.99359531 |

**Conclusion:**

All three models have performed well, Linear Regression performed the best. It perfectly fit the training data and performed well on unseen data. Lasso Regression and Random Forest Regressor also achieved good results, but they were slightly less accurate than Linear Regression.

After Understanding PCA e Linear Regression and Lasso Regression and Random Forest Regressor, we will now use only the principal features of our datasets to predict population growth and crime rates.

First, we will predict the population growth for the next 8 years using simple linear regression, then, we will use this result as an input to a lasso regression model to predict crime rates for the next 8 years.

## 3.3 Predicting Population growth:

For this purpose, I’ve created a new model, “lr\_pop” that utilize simple regression, since we have only the Year and Population.

After, I’ve created a new dataframe with a range of years from 2023 to 2030, and applied the model “lr\_pop” to predict the population.

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Subsequently, I employed the outcome in a new model, "lasso\_crime," which estimates crime rates based on population demographics.

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**Result**:

As a result, using linear regression and lasso regression, we could predict well that crime rates would decline over the next seven years. This is a positive trend, and it suggests that the model is able to identify factors that are contributing to the current crime rate and that these factors are likely to change in the future.

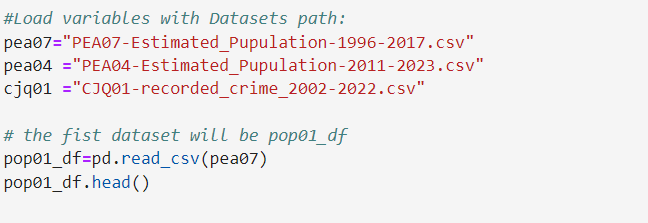
# 4.0 Programing

## 4.1 Programming Paradigms

Through the development of this project, Imperative programming, functional programming and object oriented programming has been aplied.

Imperative programming was applied in tasks such: reading and writing data to and from CSV files, Performing data cleaning and preprocessing operations.

This is an example of imperative programming, it tells the computer how to perform the task step by step.

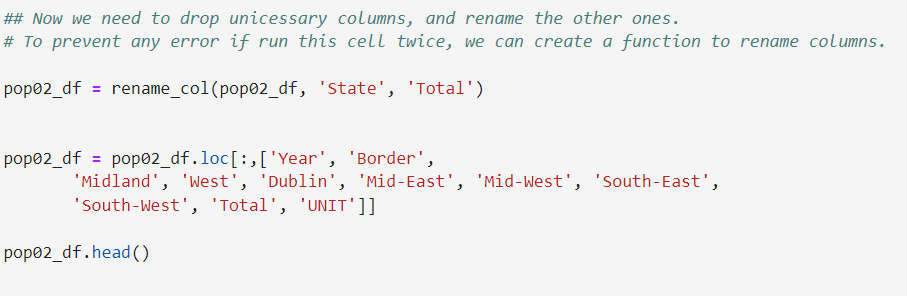


Functional programming was applied to tasks such: filtering and manipulating data frames using pandas and creating and applying custom functions, for example, rename\_col().

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Object-oriented programming: I used object-oriented programming to organize my code into reusable and maintainable classes and objects. For example, I reused the function to rename columns.



Programming paradigms was used to merging the population datasets, as the result of the merge was different columns, I used functional programming to create a function to rename the columns, this was one specific problem that I solved using programming knowledge.

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Moreover, I created a function to calculate outliers and applied a for loop to execute this function in each column.

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## 4.2 Benefits of using different programming paradigms.

By using different programming paradigms will increase the performance of the code, as well as, the reusability.

Functional programming and object-oriented programming allow to create code more reusable and maintainable. For example, create functions and classes that can be used to perform common tasks, such as data cleaning and data visualization.

Furthermore, applying different programing paradigms and commenting the code, improve the readability, it makes the code more readable and easier to understand.

A screenshot of a computer program

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# 5.0 Bibliography

*McKinney, W., 2011*. pandas: a Foundational Python Library for Data Analysis and Statistics.

Severance, Charles R, Python for Everybody, Exploring Data Using Python 3

Fox, Emily. Lasso Regression: Regularization for feature selection, CSE 446: Machine Learning, University of Washington, January 18, 2017

A Step-by-Step Explanation of Principal Component Analysis (PCA), Zakaria Jaadi, https://builtin.com/data-science/step-step-explanation-principal-component-analysis [Accessed 18 October 2023].

Functional programming vs. imperative programming (LINQ to XML), Available at https://learn.microsoft.com/en-us/dotnet/standard/linq/functional-vs-imperative-programming [[Accessed 10 October 2023].

Turney ,Shaun . Skewness: Definition, Examples & Formula, Available at https://www.scribbr.com/statistics/skewness/ Published on May 10, 2022, Revised on June 22, 2023. [Acessed on 15 october 2023].

Pattnaik, Satyajit. Skewness and Kurtosis in Statistics | What is Skewness? | Handle Skewness | Satyajit Pattnaik [Video]. https://www.youtube.com/watch?v=OizqFlMtZLQ [Acessed on 15 October 2023].

**Datafile sources:**

Available at <https://data.cso.ie/> [Accessed on 5 October 2023]