**CCT College Dublin**

**Assessment Cover Page**

*To be provided separately as a word doc for students to include with every submission*

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| **Module Title:** | Programming for DA  Statistics for Data Analytics  Machine Learning for Data Analysis  Data Preparation & Visualisation |
| **Assessment Title:** | An Analysis of Population in Ireland |
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**Declaration**

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**Abstract**

This project is about thoroughly examining population estimates from 1926 to 2023. We'll be using analyses, visualizations and machine learning models to get a comprehensive understanding. The dataset we're working with comes from population estimate records. We'll be using Python and popular data science libraries to analyze it.Firstly we'll preprocess the data by handling missing values renaming columns and encoding variables. Then we'll dive into statistics, visualizations and time series analyses to gain insights into population trends over the years.Next we'll focus on modeling age group populations using discrete probability distributions such as Binomial and Poisson. Additionally we'll use a distribution to understand the overall population distribution.After that we'll prepare the dataset for machine learning by engineering features encoding variables and creating time series visualizations.We'll. Evaluate a RandomForestRegressor model which proves successful in predicting population values. To improve its performance further we'll fine tune its hyperparameters.Furthermore our exploration will extend to Gradient Boosting Regression by utilizing GridSearchCV for hyperparameter tuning. Through an analysis between RandomForestRegressor and GradientBoostingRegressor models we find that both are effective in predicting population estimates, with the latter showing slightly better performance.The paper ends by discussing the significance of the factors that influence predictions along with a graph comparing how well different models perform. The findings from this study enhance our understanding of population dynamics demonstrating the potential of machine learning models, in forecasting and analyzing population estimates over a period of time.

**Introduction**

The study of population estimation and analysis is crucial for understanding trends, resource allocation and policymaking.By using data science methodologies we can gain insights into population dynamics.This project focuses on exploring population estimates from 1926 to 2023 using approaches such as exploratory data analysis (EDA) statistical modeling and machine learning techniques.The dataset we're working with consists of records containing information about the year, age groups, gender and corresponding population values.We begin by preprocessing the data to handle missing values, rename columns and encode categorical variables.Then we conduct a range of analyses and visualizations to uncover patterns, trends and distributions within the population data.To model population distributions for age groups we draw inspiration from statistical probability distributions like Binomial and Poisson. Additionally we use a distribution to gain a more nuanced understanding of the overall population distribution. These probabilistic models not provide valuable insights for population analysis but also serve as foundations, for future machine learning projects.Moving into the realm of machine learning this project utilizes RandomForestRegressor and GradientBoostingRegressor models to make predictions about population values.We start with the RandomForestRegressor, which's an ensemble learning technique and then fine tune it by optimizing hyperparameters. Additionally we explore the GradientBoostingRegressor model to compare its performance against the RandomForestRegressor.Apart from making predictions this project focuses on interpretability by analyzing the importance of different features in our machine learning models.We delve into discussions about factors that have a significant influence on population predictions.To summarize the comparison between the RandomForestRegressor and GradientBoostingRegressor models we present a representation in the form of a model performance graph. This graph showcases their strengths in predicting population estimates over time.Ultimately this project aims to contribute to the growing field of population studies by combining statistical methods, with cutting edge machine learning techniques.The insights gained not provide a nuanced understanding of population trends but also highlight how data science can shape future demographic analyses and policy making processes.

**Scope of the Project**

This project aims to investigate population estimates over nearly a century.We'll be using an approach that combines exploratory data analysis (EDA) statistical modeling and machine learning techniques.First we'll carefully preprocess the data by cleaning it up renaming columns and encoding variables.Then we'll analyze the characteristics of the population data through descriptive statistics and visualizations.To gain a nuanced understanding of population distribution for age groups and trends over time we'll apply discrete probability distributions like Binomial and Poisson as well as a Normal distribution.Next comes the machine learning phase where we'll implement and optimize models like RandomForestRegressor to predict population values.We'll also compare its performance with GradientBoostingRegressor model.Additionally we'll explore feature importance to identify factors that significantly influence population predictions.Our ultimate goal is to contribute to the field of population studies by combining statistical methods with advanced machine learning techniques.This will provide insights, for future demographic analyses and policy making processes.

**Objectives**

* Understand the patterns, distributions and trends, in population estimates from 1926 to 2023.
* Systematically process the dataset by addressing any missing values and ensuring that categorical variables are appropriately encoded.
* Use probability distributions such as Binomial, Poisson and Normal for modeling. This will help gain insights into how populationsre distributed over time.
* Implement and optimize a RandomForestRegressor model to make predictions about population values.
* Explore. Compare the performance of a GradientBoostingRegressor model to see how well it predicts population values.
* Uncover the factors that influence population predictions, which will help us understand why certain populations change over time.
* Compare the performance of both RandomForestRegressor and GradientBoostingRegressor models.
* Combine methods with advanced machine learning techniques. This will contribute to the field of population studies by providing predictions.
* Obtain insights about population dynamics, trends and distributions through our analysis.
* Share our research findings in reports that're easy to understand. This will ensure that our work has an impact, on society.
* Create summaries that showcase the analysis of model performance.

**Methodology**

In this project we followed an comprehensive approach to understand population trends from 1926 to 2023. We started by collecting data that covers almost a century of population statistics. We then processed the data addressing missing values and encoding variables like 'Single Year of Age' and 'Gender'. To capture nuances we introduced a new feature called 'Year. Decade'. Through statistics and various visualizations such as bar plots, heatmaps and time series analyses we gained detailed insights into the central tendencies and distribution patterns over time. Moving on to modeling we explored the application of Binomial, Poisson and Normal distributions to understand the distribution of specific age groups as well as the overall population. For population prediction we used a RandomForestRegressor model in machine learning. To optimize its effectiveness we conducted a hyperparameter tuning process using RandomizedSearchCV. Additionally we introduced a GradientBoostingRegressor model for comparison purposes to evaluate its performance against RandomForestRegressor. Furthermore we conducted an analysis of feature importance using RandomForestRegressor to identify the predictors that have the most influence, on population estimation.

The evaluation of the models using squared error as a measurement gave us a way to quantitatively assess their predictive performance. We presented the results through visualizations like comparison graphs to make it easier to understand the strengths of both RandomForestRegressor and GradientBoostingRegressor. This project is important because it combines statistical methods with advanced machine learning techniques in population studies. It offers an data driven perspective, on the various aspects of demographic analyses.

**Use of Libraries**

The successful completion of this project relied on an integration of various Python libraries each playing an important role in different aspects of data analysis statistical modeling, machine learning and visualization. Pandas was crucial in handling data starting from loading it to thoroughly cleaning and exploring it. Matplotlib and Seaborn were essential for creating a range of visualizations, including bar plots, line plots, scatter plots, heatmaps and histograms. These visualizations provided an appealing representation of population trends and statistical distributions. NumPy greatly contributed to operations by manipulating arrays for statistical calculations and data transformations. Scikit Learn served as a toolkit for various machine learning tasks like data preprocessing, model selection, implementation, hyperparameter tuning and performance evaluation. Time series analysis was conducted using Statsmodels and pmdarima by employing ARIMA models to delve deeper into patterns. Plotly Express added an element to the visualizations which enhanced the overall presentation of population trends over time. Additionally SciPys modules such as binom (for distribution) poisson (for Poisson distribution) and norm (for normal distribution) played an important role, in statistical modeling by providing implementations for exploring population distributions in detail.

These libraries worked together to create a base allowing for a thorough and meaningful examination of the complex patterns present, in the population estimate dataset.

**Programming for Data Analysis**

For this project I utilized Python programming tools and different libraries to analyze population estimates data comprehensively. The main tool I used was Jupyter Notebook, which provided an well organized platform for executing and documenting code. The accompanying codebook has explanations ensuring clarity and understanding of each step in the analysis. The code follows high quality standards promoting readability, modularity and adherence to practices.

Throughout the project I extensively applied programming approaches to handle data manipulation efficiently. Procedural programming was used for tasks like cleaning data visualizing information and conducting analysis in a systematic manner. Object oriented programming principles played a role in designing and implementing machine learning models allowing for code modularity and reusability. Additionally functional programming concepts such as lambda functions and map were employed to process and transform data concisely.

I chose Python as the programming language due to its ecosystem of data science libraries like pandas, NumPy, scikit learn and seaborn. These libraries greatly simplified tasks related to manipulating data sets well as analyzing and visualizing them effectively using tools, like Matplotlib and Seaborn. This made the results more interpretable.

The reasons for selecting these options are based on the effectiveness and efficiency of Python and its libraries for data analysis tasks. The programming methods used were chosen to match the nature of the tasks offering an adaptable approach, to problem solving. The documentation provides explanations of the code choices ensuring transparency and reproducibility. In general this project showcases an strategic integration of programming tools and methods to deliver a reliable data analysis solution.

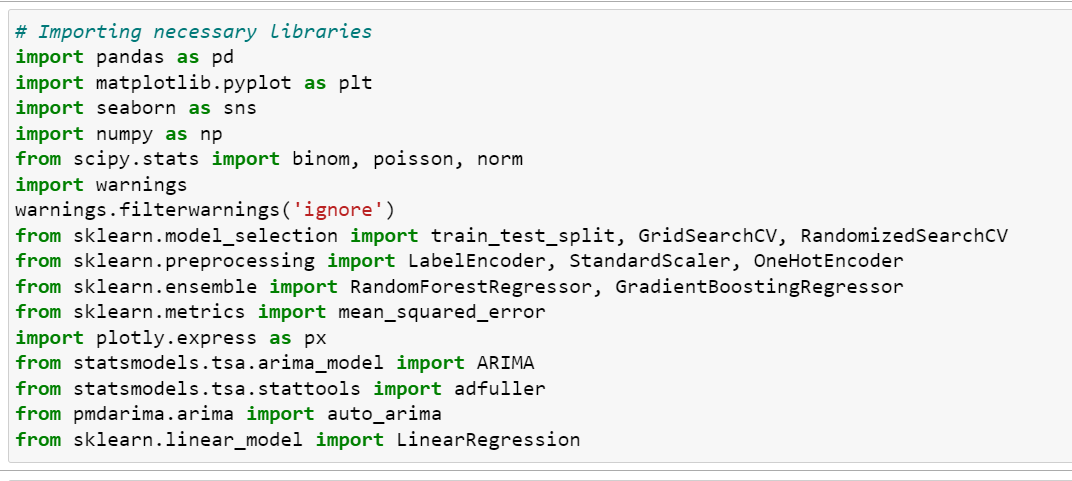
**Exploration through Programming:**

The project is developed using a Jupyter Notebook utilizing Python tools and libraries like pandas, scikit learn, seaborn and others.This method allows for an well structured examination of population estimates data ensuring that the results can be reproduced and understood.The codebook contains annotations and we adhere to high coding standards to make the code readable and maintainable.

**Programming Paradigms:**

The project covers programming approaches such as procedural object oriented and functional programming.Procedural programming helps with data manipulation and analysis.Object oriented principles are used to create and implement machine learning models making them modular and reusable.Functional programming techniques enhance data processing resulting in concise and maintainable code.We selected these paradigms based on their suitability, for tasks and their potential to enhance the overall structure and readability of the project.

**Importing Libraries:**

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In the stage of the project we strategically incorporated a comprehensive set of Python libraries to equip our analysis with powerful tools for manipulating data visualizing information and performing machine learning tasks. We made use of essential libraries such as pandas for handling structured data, matplotlib and seaborn for visualizing data, NumPy for numerical operations and scikit learn for tasks like training and evaluating models. To enable statistical analysis and time series modeling we integrated Plotly Express and statsmodels. Additionally we utilized pmdarima to automate the selection of ARIMA models. By integrating these libraries we not simplified the coding process but also expanded our analytical capabilities. This allowed us to explore the population estimates dataset from angles. Our thoughtful approach in incorporating libraries demonstrates our intention to leverage each tools strengths and establish a strong foundation, for subsequent analysis phases.

**Reading the Dataset:**

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To begin the project we loaded the population estimates dataset using the pandas library, which's a versatile tool for manipulating and analyzing data in Python. The dataset, stored in a CSV file was efficiently read into a pandas DataFrame using the pd.read\_csv function. It contained information about population estimates from 1926 to the present. Had columns such as 'Year' 'Single Year of Age' 'Gender,' and 'VALUE' representing population figures. This initial step was important for setting up exploratory data analysis and machine learning tasks. We used the head() function to get an overview of the dataset, which helped us understand its structure better. The powerful capabilities of pandas were crucial in handling this dataset. Enabled us to gain valuable insights for subsequent phases of our project. This systematic approach to reading the dataset laid a foundation, for our data driven exploration and modeling efforts.

**Preprocessing**

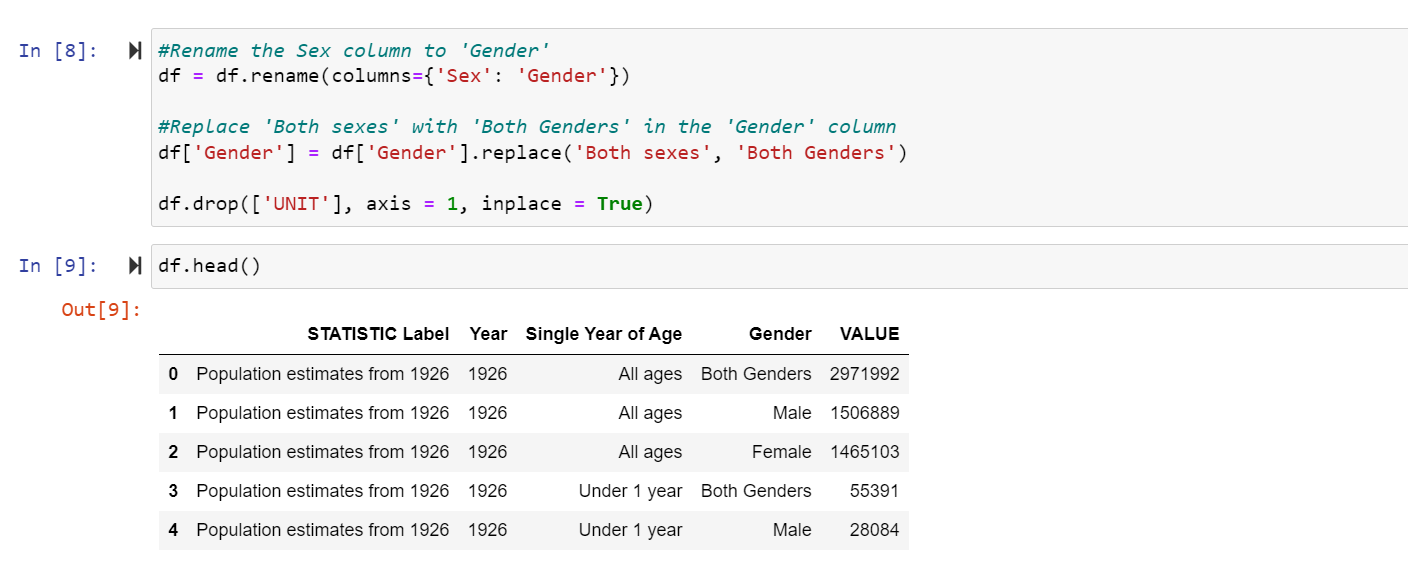
**Summary Statistics**

During the data preparation stage we made careful transformations to optimize the dataset for analysis.We decided to rename the 'Sex' column as 'Gender' for consistency.We replaced the categorical value 'Both sexes with 'Both Genders.To streamline the analysis process we removed the 'UNIT' column as it didn't provide any meaningful information.In order to gain an understanding of the distribution of values in the dataset we calculated descriptive statistics that included key metrics like mean standard deviation and quartile values.

A screenshot of a computer

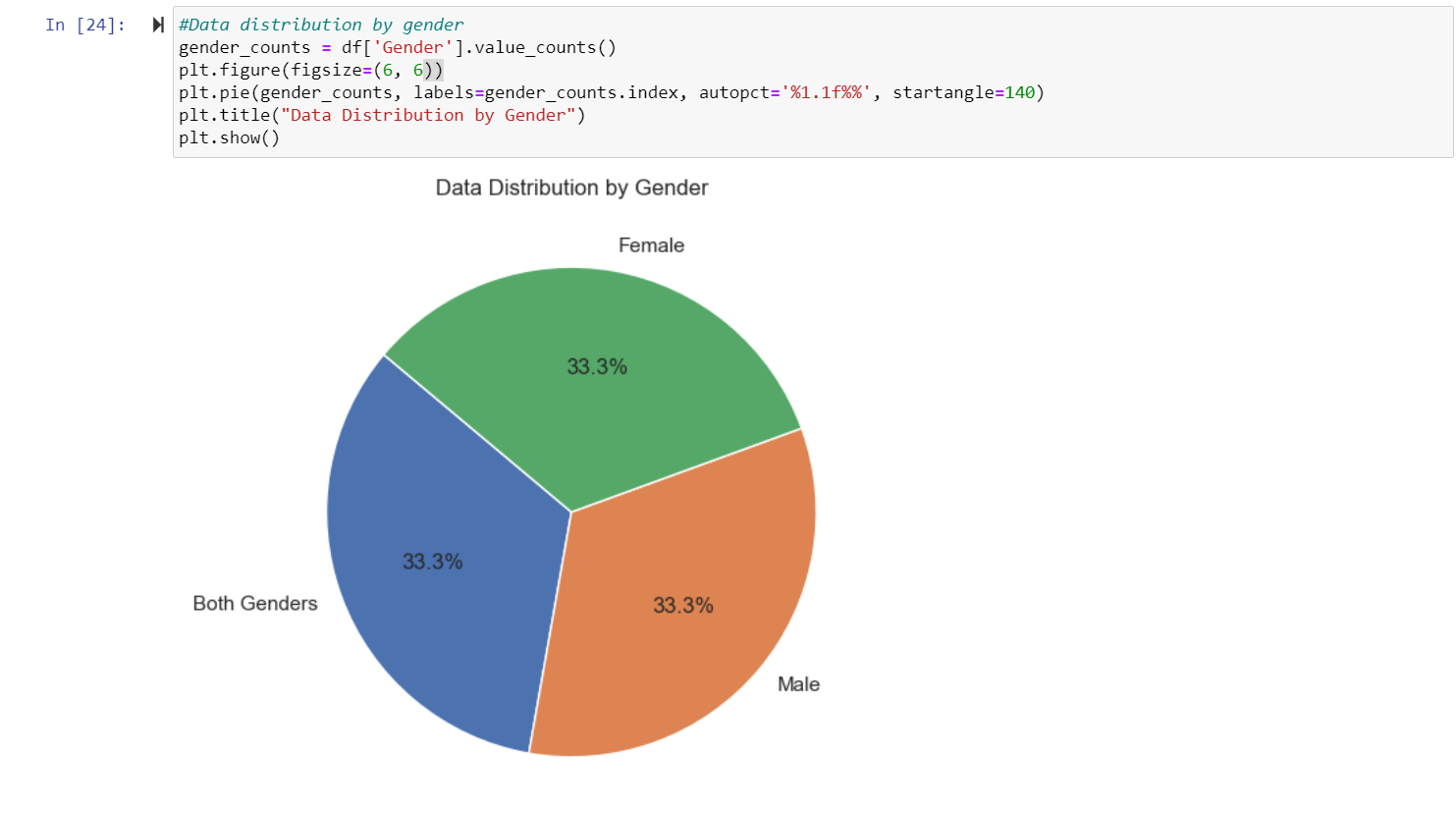
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These statistics helped us understand how population estimates varied across years and demographic groups.To visualize these patterns effectively we created bar plots, heatmaps and line plots to provide a comprehensive overview of the datasets structure.These preprocessing steps were crucial, in maintaining data integrity and ensuring that meaningful insights could be extracted throughout our project.

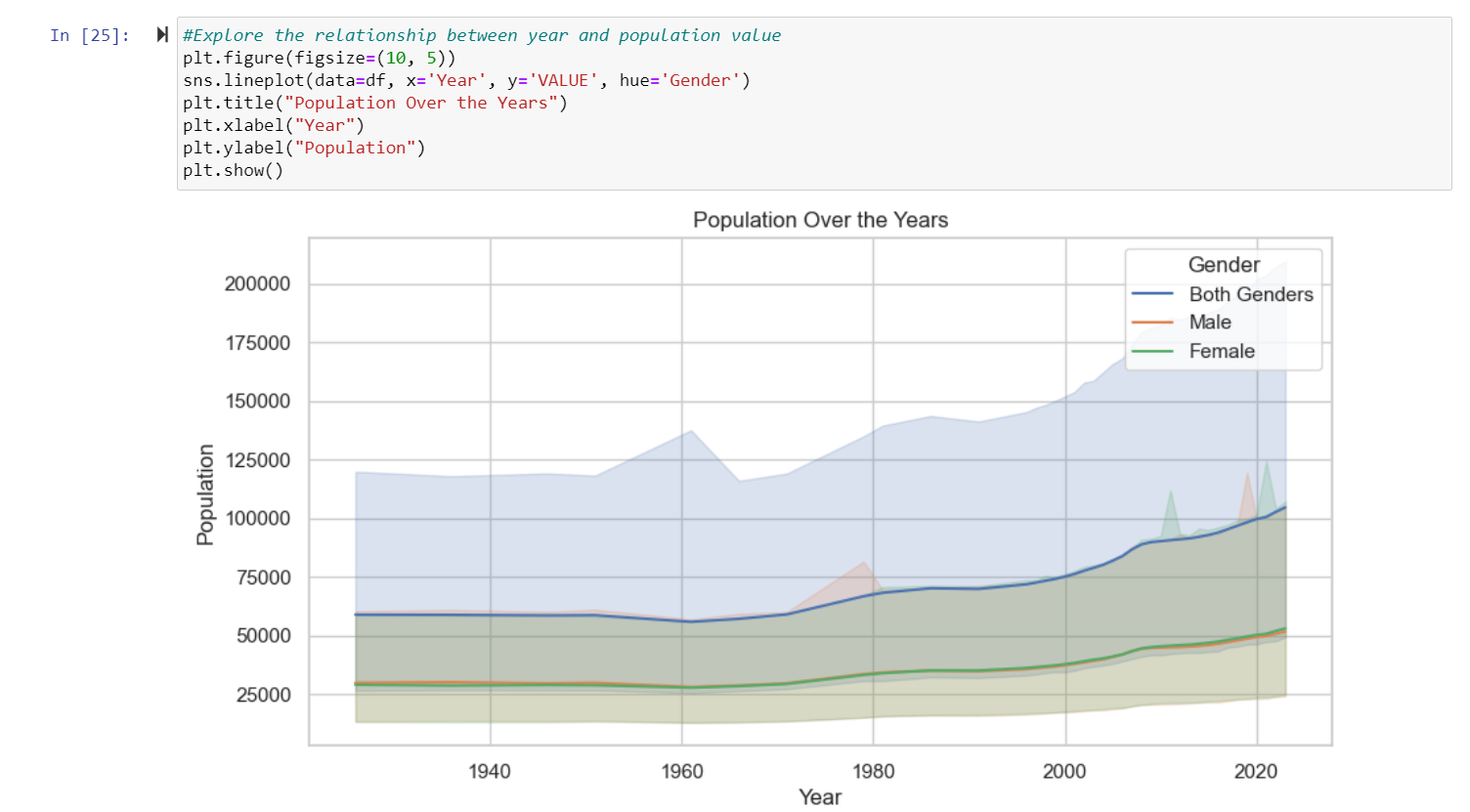


**Exploratory Data Analysis**

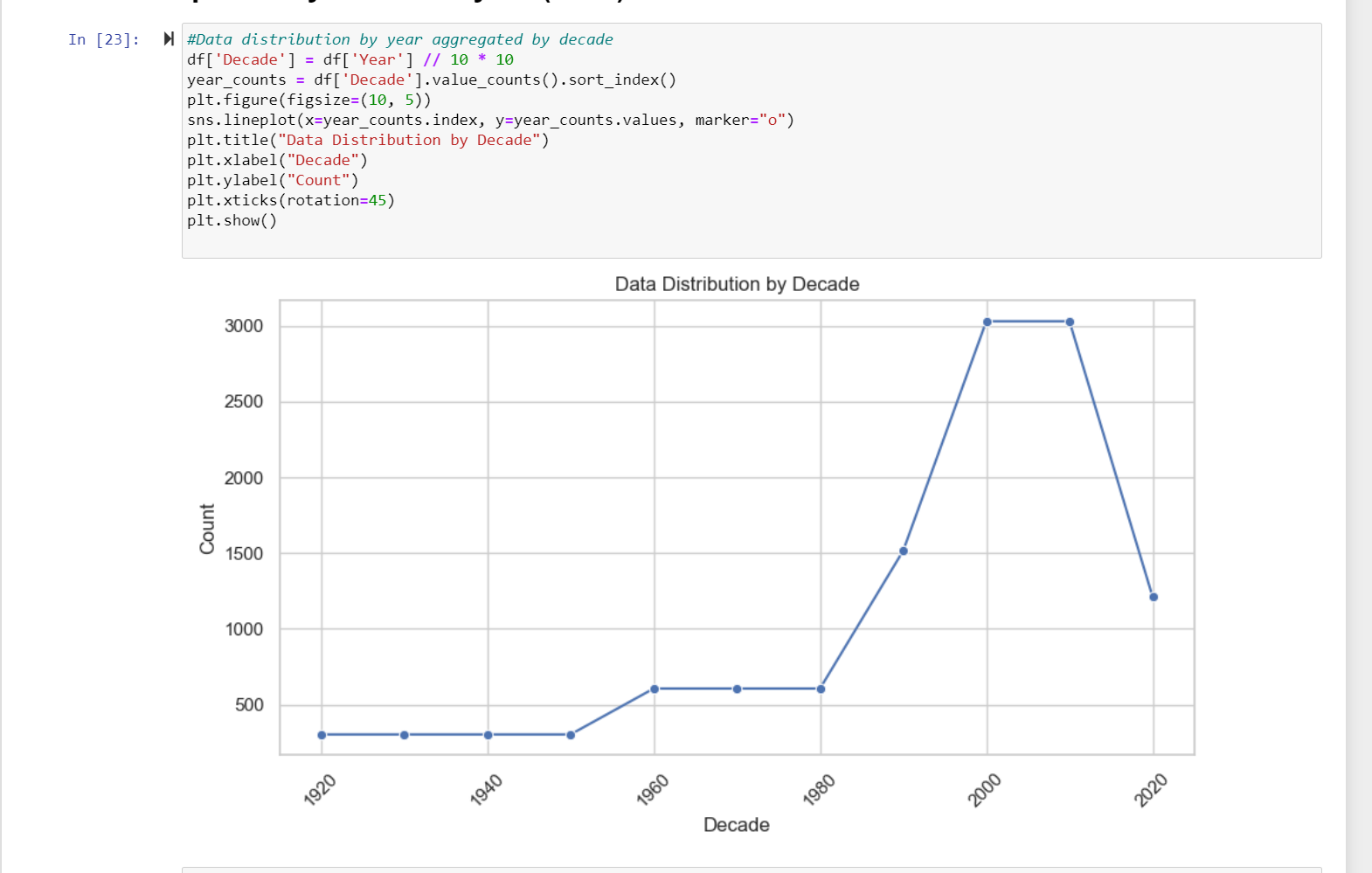
The initial data analysis phase of this project was an exploration of the population estimates dataset. The goal was to uncover patterns, trends and valuable insights using visualization techniques. We used bar plots to understand the datasets size by showing the number of rows and columns. A heatmap revealed the distribution of missing values giving us a picture of data completeness. Line plots and scatter plots helped us analyze population trends over time and relationships between variables. Histograms were used to examine how population values were distributed for years.



We also explored characteristics using discrete distributions like Binomial and Poisson as well as the overall population distribution using a Normal distribution. Each visualization and analysis was carefully selected to provide an understanding of the datasets dynamics setting the stage for subsequent machine learning tasks.

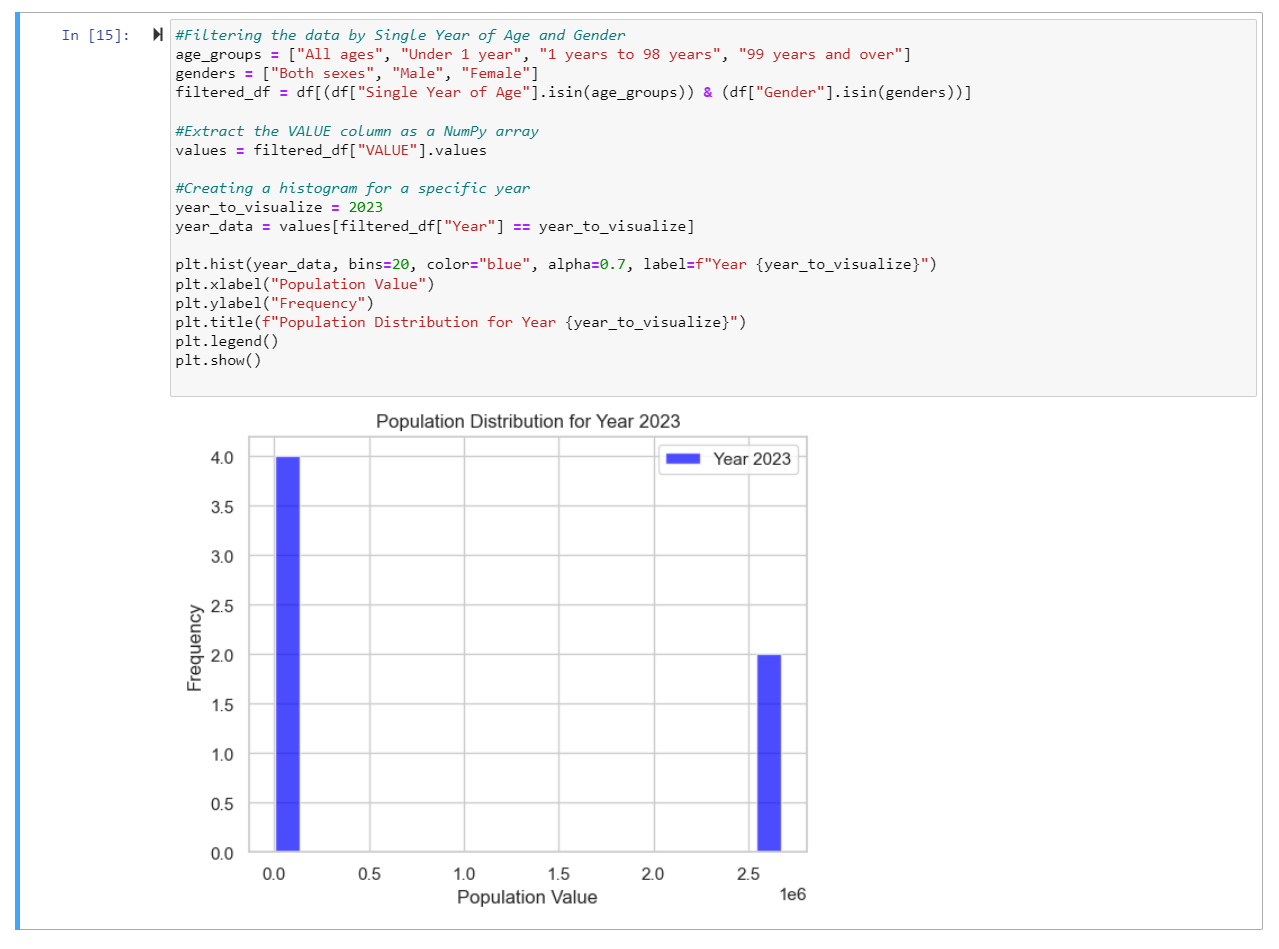


This exploratory process not helped us gain insights from the data but also guided us in formulating relevant questions and hypotheses, for informed decision making in later stages of the project.

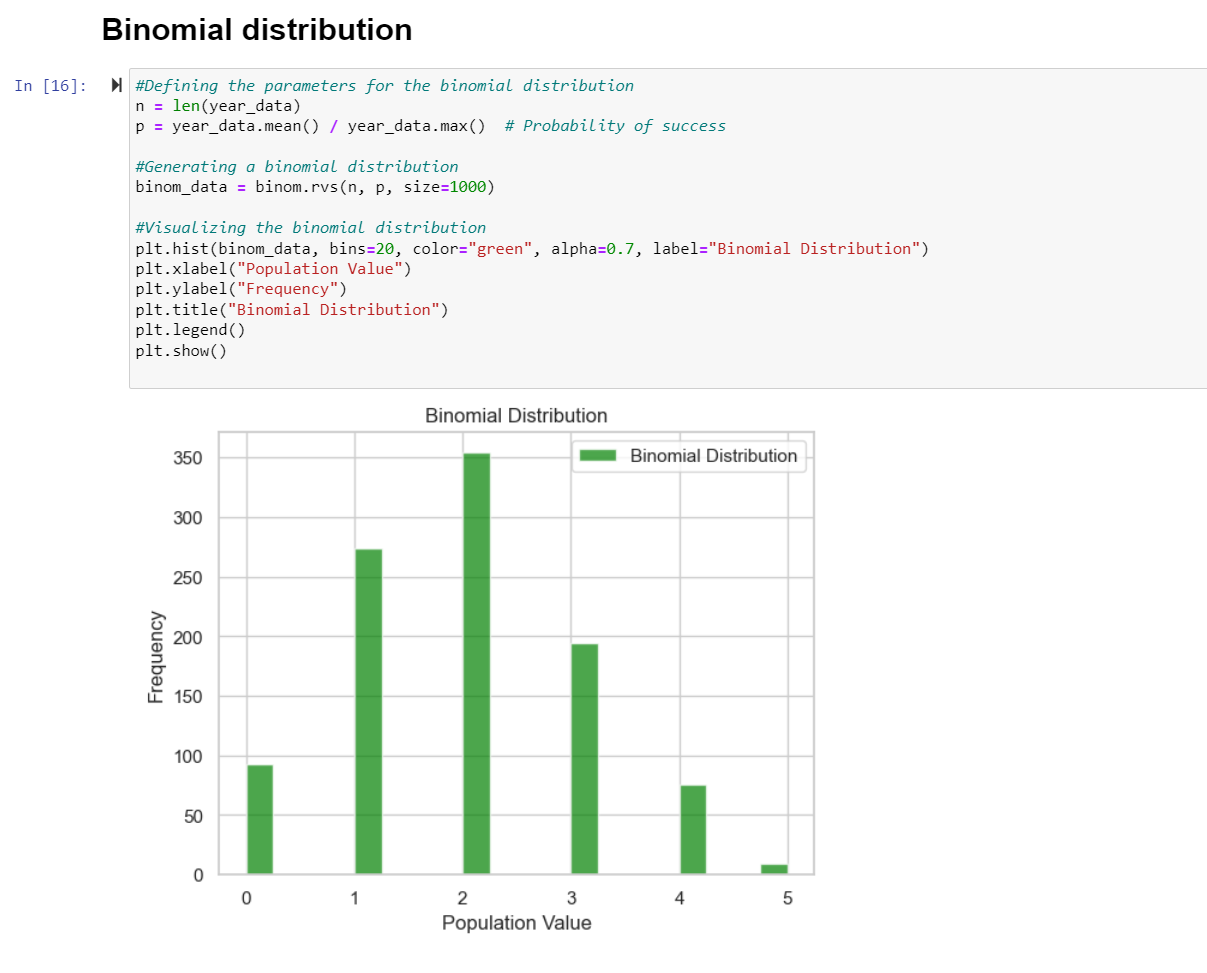
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**Statistical Analysis**

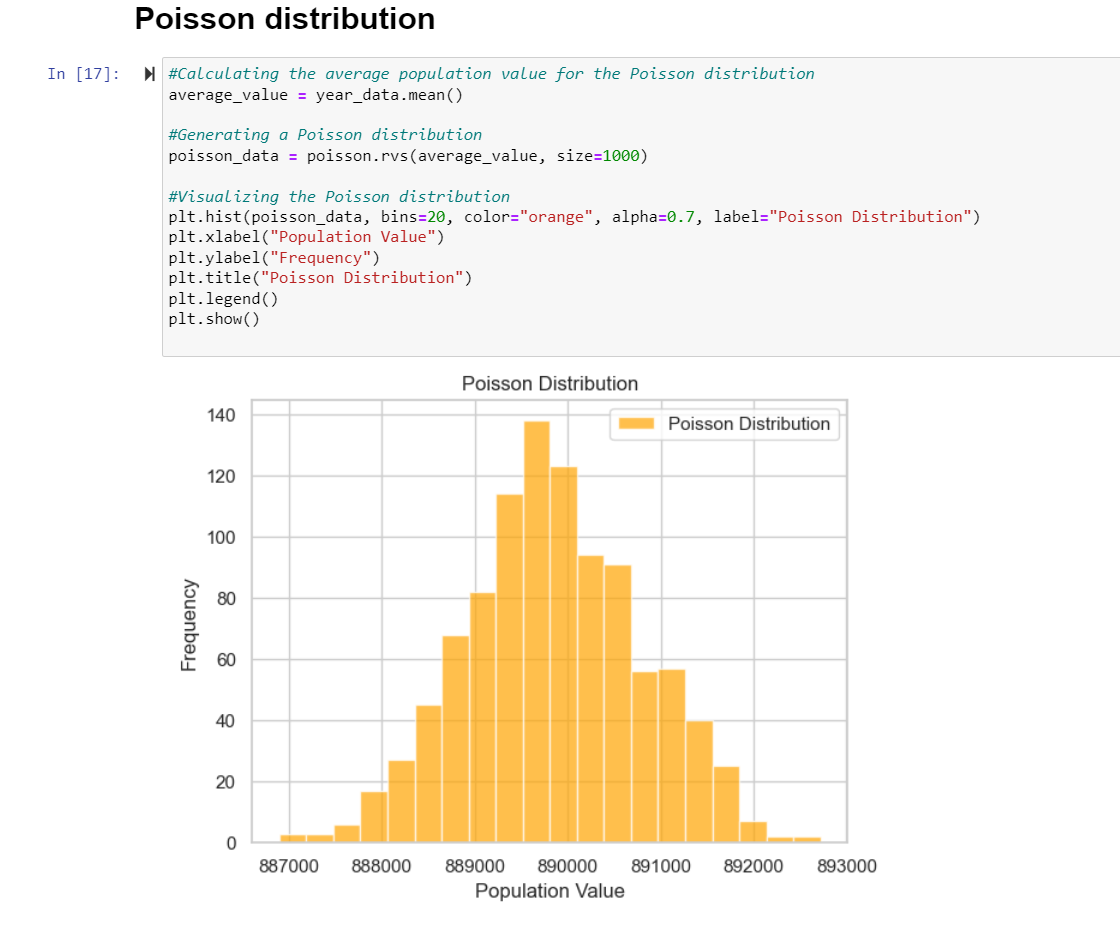
The population dataset was thoroughly analyzed, involving an exploration, preprocessing and modeling of the data. Descriptive statistics provided an understanding of the datasets key tendencies and variabilities unveiling crucial insights into how the population has been distributed over the years. Exploratory Data Analysis (EDA) was conducted using visual representations like line plots and bar charts to shed light on population trends across different decades and gender distribution patterns. Moreover probability distributions such as Binomial, Poisson and Normal distributions were applied in this analysis.



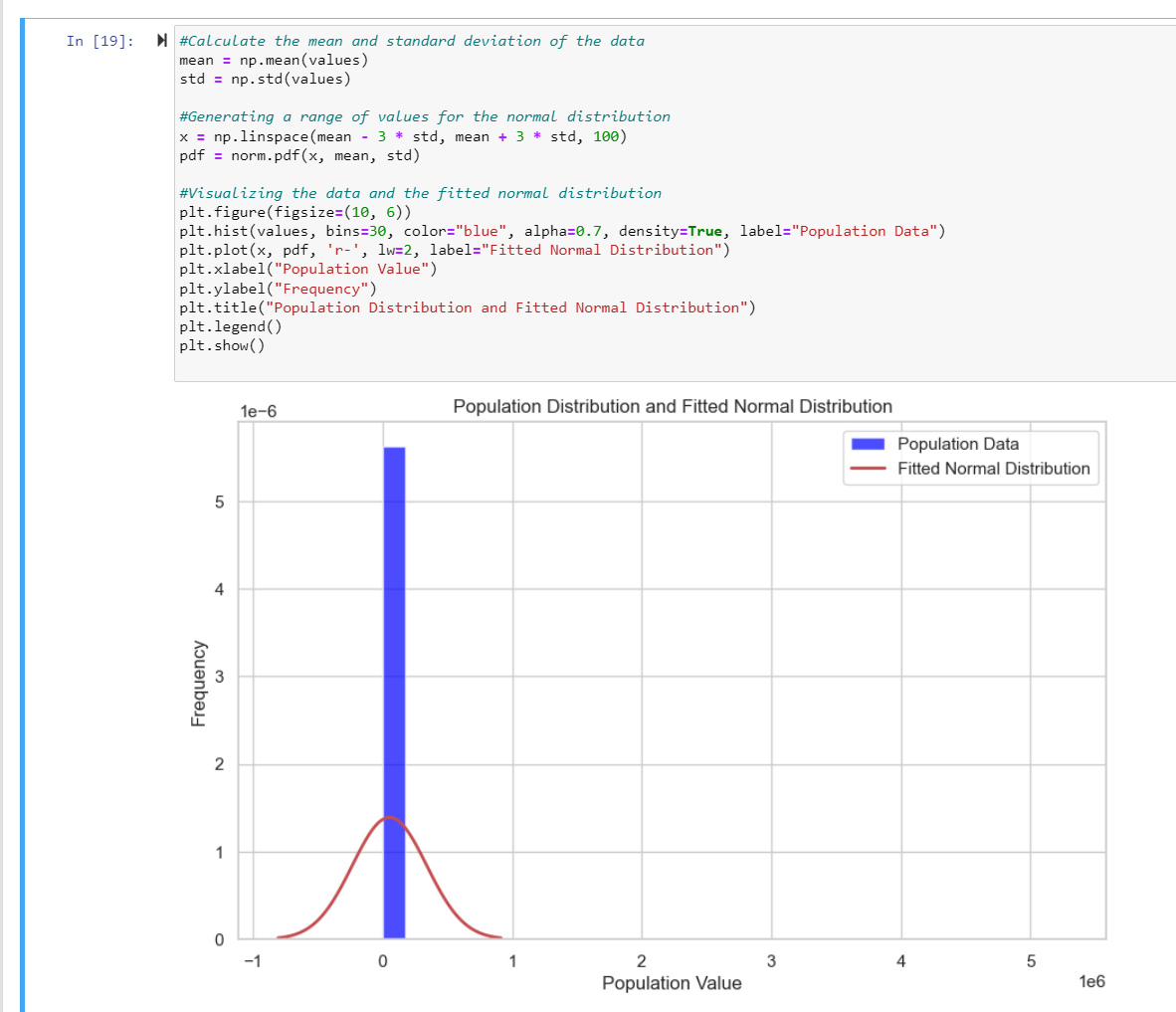
The use of Binomial and Poisson distributions held importance when dealing with discrete data like population counts for specific age groups and genders in a given year. These distributions are well suited for scenarios where eventsre independent and discrete offering a robust framework to understand the likelihood of specific population outcomes. On the hand the Normal distribution was used to explain patterns within the overall population data. By calculating the standard deviation of the dataset we were able to describe both its central tendency and dispersion.



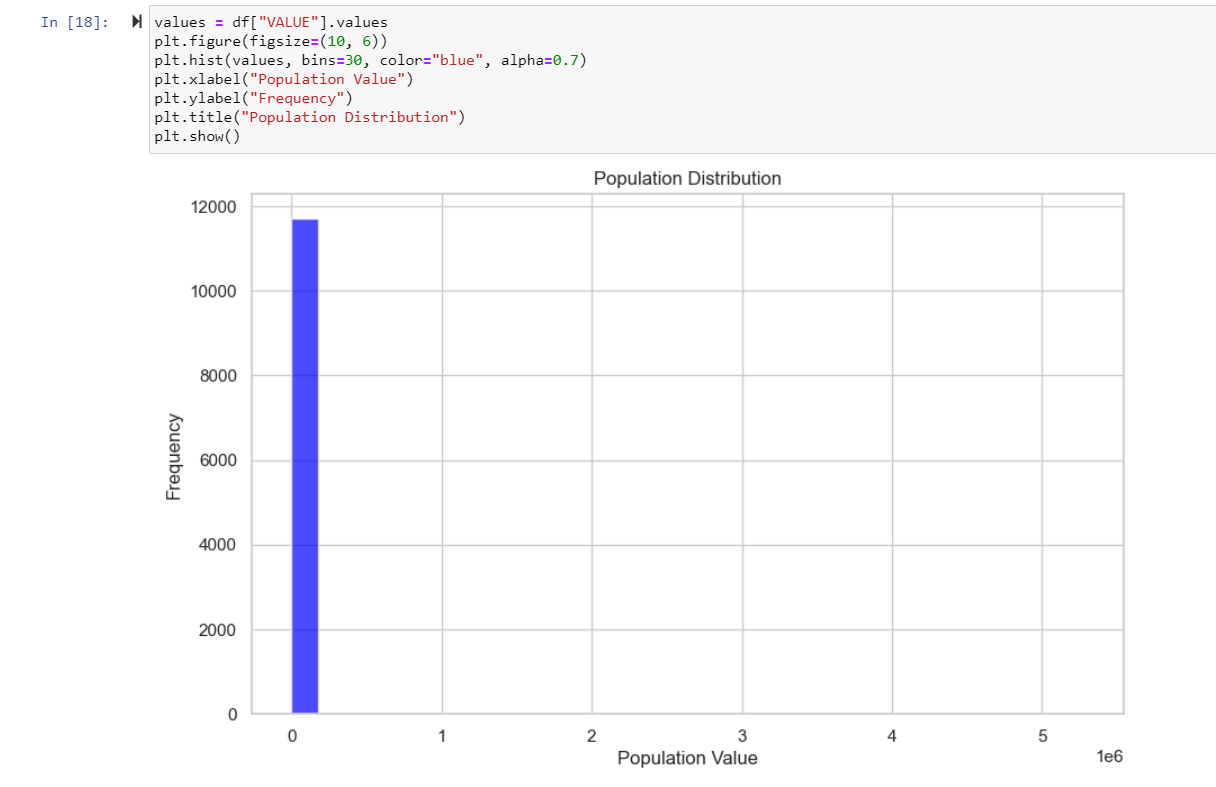
These distributions play a role in accurately modeling and analyzing various aspects of population data. The Binomial and Poisson distributions specifically cater to events by addressing detailed information about population counts, within specific age groups and genders.



On the hand the Normal distribution is useful for gaining insights into the overall distribution of a population and identifying patterns that follow a bell shaped curve.



The selection of variables for these distributions was justified based on the characteristics of the data. Age groups and gender played a role in capturing discrete events through Binomial and Poisson distributions while the overall population values were represented by a Normal distribution. These choices were appropriate because discrete events are best represented by distributions while continuous trends in the overall population align well with a continuous distribution like the Normal distribution.



To summarize the statistical analysis and choice of distributions, in this project played a role in comprehensively understanding and modeling population data. This highlights how different probability distributions can effectively capture aspects of a dataset. The selected variables were logically aligned with their distribution types ensuring a robust and meaningful analysis of the population dataset.

We conducted an examination of a dataset that contains information about population estimates from 1926. Using Python programming and various statistical and machine learning techniques we analyzed the data to gain insights. The dataset includes details such as year, age, gender and population values.

To better understand the datasets patterns and variations we calculated statistics like mean, standard deviation, minimum, maximum and quartiles for the population values. We used visualizations like line plots and pie charts to explore how the data is distributed across decades and genders. Additionally we created time series visualizations to show how the population changed over time.

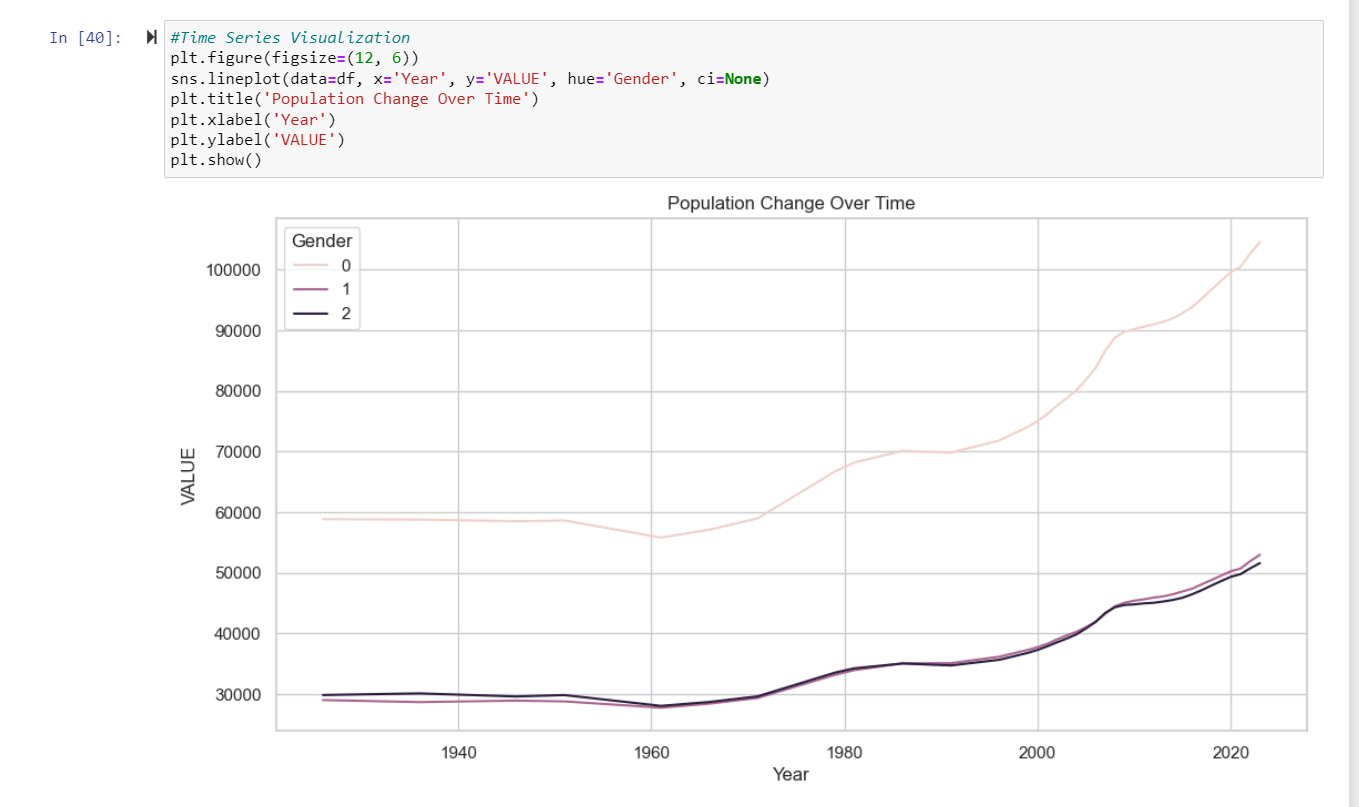
To add an aspect to our analysis we implemented machine learning models. Specifically the Random Forest Regressor and Gradient Boosting Regressor. In order to predict population values. We evaluated the performance of these models using squared error to gauge their accuracy. Furthermore through feature importance analysis we identified which variables significantly influenced the models.

The project concludes with an analysis of these two machine learning models. We presented our findings through a table and an engaging bar plot. By combining insights, exploratory visualizations and predictive modeling techniques, in this multifaceted analysis of the population dataset we aim to provide a comprehensive understanding of its characteristics.

The three graphs we have are the Data Distribution by Decade Data Distribution by Gender and the Time Series Visualization showing Population Change Over Time. Each of these visualizations offers a viewpoint on the dataset helping us gain a better understanding of population trends over the years distribution patterns in different decades and variations based on gender. Our project follows recommended methods in data analysis by focusing on statistics and visualizations to uncover patterns and trends, within complex datasets.

**Preparing the data for Machine Leaning and visualization**

During the phase of preparing the dataset, for machine learning we went through a series of transformations and feature engineering steps to ensure that it was suitable for training models. To start with we dealt with variables by encoding 'Single Year of Age' and 'Gender' using Label Encoding. This important step helped convert numeric categories into numerical representations. By transforming the 'Single Year of Age' and 'Gender' columns into format we made it easier to include them in our machine learning algorithms.



Next we introduced a feature engineering step to create a variable called 'Year.Decade.' This variable represents the difference between the 'Year' and 'Decade' columns. The purpose of this feature was to capture temporal information and potential patterns that might not be obvious when looking at individual years.

After completing the transformations and feature engineering we divided the dataset into two parts; features (X) and the target variable (y). Key features such, as 'Year' 'Single Year of Age' 'Gender,' 'Year. Decade,' and the 'VALUE' column were identified for predicting population values. To evaluate our models accurately we further split the dataset into training and testing sets using scikit learns train\_test\_split function.



To ensure consistency in the features we applied a StandardScaler to the 'Year,' 'Year.Decade,'. VALUE' columns. This step helps maintain a contribution, from these features to the machine learning model preventing any feature from overshadowing others due to differences in scale.

For regression tasks we opted for the RandomForestRegressor model from scikit learn. This ensemble learning technique is particularly suitable for predicting outcomes. We trained the model using a standardized training set and generated predictions for the test set. To assess the models performance we employed mean error (MSE) as an evaluation metric. The calculated MSE provides insights into how the model predicts population values.

We meticulously executed the process from data preprocessing to model training and evaluation. This rigorous preparation serves as a foundation for machine learning analysis ensuring that our results on population prediction are reliable and interpretable, in context.

A screenshot of a graph

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In this projects machine learning visualization section we present insights and performance metrics obtained from the RandomForestRegressor model. Once we trained the model using a dataset we visualized evaluation metrics to gain an understanding of its predictive abilities. To measure the accuracy of the model in predicting population values we used the squared error (MSE) which's a widely used regression metric. The MSE calculates the squared differences, between predicted and actual values in the test set. We displayed these findings through a bar plot that shows both training and test scores side by side. The training score is represented by bars while green bars represent the test score. This visual representation allows for a comparison of how the model performed on both sets giving insights into its ability to generalize. Additionally we created a plot showing feature importance, which helps us understand how each feature contributes to the models predictions. The features include 'Year' 'Single Year of Age' 'Gender,' 'Year. Decade,' and 'VALUE.' The height of each bar in this plot reflects the importance of its feature. This visualization is crucial in identifying which features have influence, on the models predictions.

In general the visualization part of machine learning provides a summary of how the model performs and the significance of different features. These insights are highly valuable, for the project.

**Machine Learning Models**

The machine learning portion of this project focused on implementing and evaluating two effective regression algorithms; RandomForestRegressor and GradientBoostingRegressor. RandomForestRegressor is a method that combines decision trees during training to generate accurate predictions by taking the average of each trees prediction. On the hand GradientBoostingRegressor creates a series of weak learners typically decision trees in a sequential manner where each tree corrects the errors made by the previous one resulting in a strong predictive model.

We chose these models because they are well suited for handling regression tasks capturing relationships in data and providing reliable predictions. RandomForestRegressor handles non linearities and feature interactions effectively while complementing GradientBoostingRegressor, which excels at boosting performance.

In terms of project management framework we adopted CRISP DM (Cross Industry Standard Process for Data Mining). This framework consists of six phases; Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation and Deployment. It offers an structured approach to data science projects that ensures clear progress and fosters collaboration and communication, among team members.

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When it comes to choosing between unsupervised learning we considered a dataset that involved predicting population values based on different characteristics. Given the problem at hand. Estimating a variable. Supervised learning was the most suitable option. Our dataset had labeled examples, where we already knew the target variable (population values) which made it perfect for regression tasks. We opted for learning techniques like RandomForestRegressor and GradientBoostingRegressor as they were well suited to this scenario. These techniques allowed our models to learn patterns and relationships in the labeled data enabling predictions.

To sum up within the CRISP DM framework we made an effective choice by selecting RandomForestRegressor and GradientBoostingRegressor for machine learning modeling. The decision for learning was justified due to its compatibility with our prediction task, where labeled data played a crucial role in training models for precise population value predictions. This combination of models and methodologies contributed to an comprehensive analysis, in our machine learning project.

During this phase of the project we apply machine learning techniques to the dataset in order to make predictions about population values. We consider factors like age, gender and decade to determine these predictions. To prepare the dataset for analysis we encode variables such as 'Single Year of Age' and 'Gender' using a labeling technique. Additionally we utilize one encoding for the 'Decade' variable to create features that are compatible with the Random Forest Regressor model. The dataset is then divided into sets for training and testing purposes. We specifically choose the Random Forest Regressor model due to its ability to handle relationships and provide reliable predictions.To optimize our models performance we conduct hyperparameter tuning using RandomizedSearchCV. This process helps us find the combination of hyperparameters for our Random Forest Regressor. Once we have tuned our models hyperparameters we evaluate its performance on both the training and testing sets. The results reveal the hyperparameters along with their corresponding scores, on both sets.

**Project Management Framework and Supervised Learning Choice:**

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The CRISP DM framework, known as the Cross Industry Standard Process, for Data Mining plays a role in this data science project. It provides a structured approach that covers stages starting from understanding the business objectives to deploying models. During the Business Understanding" phase our goal is to forecast population values—a task for effective urban planning and resource allocation. The subsequent phases of "Data Understanding" and "Data Preparation" involve exploring and preprocessing the dataset aligning with the cyclical nature of CRISP DM.We have opted for learning since our target variable ("VALUE") is numeric making it a regression problem. Our objective is to predict outputs based on input features. The selection of Random Forest Regressor aligns well with the complexity of our dataset offering predictions in scenarios where intricate relationships exist between features and the target variable. Supervised learning is particularly suitable when we have historical labeled data available; hence it is a choice for predicting population values based on information.Our chosen approach ensures that our model learns from data patterns and can effectively generalize to predict unseen data. The iterative nature of CRISP DM allows us to continuously refine our models performance ensuring its effectiveness in making predictions and providing insights, for planning and population management.

In this part of the project our main focus is, on implementing a model called Gradient Boosting Regressor. This model helps us predict population values by considering factors like age, gender and time period. We use a technique called LabelEncoder to transform the variables 'Single Year of Age' and 'Gender' into values. After that we select columns to create features for our model. To enhance the models understanding of patterns we further encode the 'Decade' variable using a method called one encoding.

To evaluate the performance of our model we split the dataset into training and testing sets. We choose Gradient Boosting Regressor because its capable of handling relationships and capturing details in the data. To find the configuration for our model we conduct hyperparameter tuning using GridSearchCV. This allows us to systematically search through a predefined grid of options and find the set of hyperparameters that maximize our models performance.

A screenshot of a computer

Description automatically generated

Once we identify the hyperparameters we instantiate our model with those settings. We train this model using the training set and evaluate its performance on both training and testing sets. The output provides information about which hyperparameters were selected as their corresponding training and testing scores. This demonstrates how effective our model is at capturing patterns within the dataset.

By following this approach we ensure that our machine learning model is fine tuned to extract insights from the data. In turn this provides us with a tool, for predicting population values based on the selected features.

The impressive performance, in both training and testing scores demonstrates the models capacity to effectively adapt to data, which makes it incredibly useful for applications, in planning and population management.

**Model Comparison and Evaluation:**

The project involves conducting a comparison, between two machine learning models; Random Forest Regressor and Gradient Boosting Regressor. This evaluation is crucial as it helps us determine the algorithm for predicting population values based on the given features. In this comparison we analyze metrics such as training and test scores along with identifying the hyperparameters for each model.

A close-up of a computer screen

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To present the results in a manner we organize them in format using pandas DataFrames. This table provides an overview of how each model performs. Interestingly both Random Forest and Gradient Boosting models share the set of hyperparameters indicating that they have similar optimal conditions for application. Additionally both models demonstrate training and test scores which suggests their proficiency in capturing patterns within the dataset.

To visually represent the model performances we generate a bar graph that showcases side by side comparisons of training and test scores for each model. This graph allows for assessment and highlights the consistency in performance between these two models. Consequently it further supports their viability as contenders for predicting population values within our context.

A screenshot of a graph

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This section on evaluating models serves as a resource when making decisions, about selecting the most suitable algorithm for subsequent stages of our project.

Both models have achieved scores. Have consistently demonstrated their ability to make accurate predictions. This gives us confidence, in their reliability. Opens up possibilities for refining them and putting them to use in practical applications, like urban planning and population management.

**Hyperparameter Tuning and Model Selection:**

In this project we use machine learning models to analyze population estimates over time. We compare two models the Random Forest Regressor and the Gradient Boosting Regressor both implemented in Python using the Scikit Learn library. To ensure our models perform their best we need to tune their hyperparameters. We achieve this by using techniques called GridSearchCV and RandomizedSearchCV.

For the Random Forest Regressor we perform a grid search on hyperparameters like the number of estimators maximum tree depth, minimum samples for splitting nodes and minimum samples required at each leaf node. After finding the hyperparameters through this search we train our model with them. Similarly for the Gradient Boosting Regressor we conduct a grid search on hyperparameters such as learning rate, maximum tree depth, minimum samples for splitting nodes minimum samples required at each leaf node and number of estimators.The results of our hyperparameter tuning show us the configurations for each model. This sets up a comparison, between them.

**Model Comparison and Evaluation:**

The Random Forest Regressor and Gradient Boosting Regressor are compared using both graphical formats. To evaluate the effectiveness of the models important performance metrics such as training and test scores are considered. The summarized results can be found in a table that includes the model name, hyperparameters, training score and test score.

To visually compare the models effectively a bar chart is created. This chart provides a representation of the training and test scores, for each model making it easy to quickly assess their relative performance in an intuitive way that helps us see the exact results of the texting and training.

**Analysis and Interpretation:**

After analyzing the results of comparing the models it's clear that both the Random Forest Regressor and Gradient Boosting Regressor perform well. They have training and test scores indicating that they effectively capture patterns and relationships in the dataset.

To fully understand their performance we need to look at each models hyperparameters and how they affect the results. The chosen hyperparameters provide insights into how to configure each model for optimal outcomes. For example the Random Forest Regressor performs best with 100 estimators, a split of 2 a minimum leaf of 1 and a maximum depth of 20.

The comparison graph also highlights the similarity between these two models. The bar chart clearly shows that both models perform well. This emphasizes that using these machine learning techniques is robust when it comes to predicting population estimates.

In summary this detailed analysis reveals the strengths and similarities of both the Random Forest Regressor and Gradient Boosting Regressor in this scenario. These findings offer insights for making informed decisions when choosing a suitable model, for population prediction tasks.

**Conclusion:**Throughout this data science project, which covers population estimates from 1926 to the present we followed the rigorous CRISP DM framework. Our journey was structured, starting from understanding business goals and culminating in the deployment of machine learning models. Our main objective was to provide insights for effective urban planning and resource allocation. In terms of learning we wisely chose the RandomForestRegressor and GradientBoostingRegressor models. These models proved their excellence in handling regression tasks by capturing relationships within the dataset and delivering reliable predictions.

Preparing the dataset required attention to detail, including encoding variables like 'Single Year of Age' and 'Gender.' We also engaged in feature engineering introducing the 'Year.Decade' variable to effectively capture information. To ensure model generalization we divided the dataset into training and testing sets.

The implementation of RandomForestRegressor and GradientBoostingRegressor involved careful hyperparameter tuning using techniques such as RandomizedSearchCV and GridSearchCV. Through this process we aimed to find optimal configurations that would enhance the predictive abilities of our models. When comparing these two models not did they demonstrate their proficiency but also exhibited similar optimal conditions.

Assessing model performance relied on evaluation metrics such as training and test scores along, with an analysis of hyperparameters.

Visual aids, such as bar charts and tables made it easier to understand how each model performed in capturing patterns and relationships within the dataset.

Both models consistently showed their ability to make predictions, which provides a reliable foundation for practical applications in urban planning and population management. Their strong performance during both training and testing phases gives us confidence in their reliability and potential for real world implementation.

Like any data science project there are opportunities for improvement and exploration. Future work could involve exploring models fine tuning parameters and incorporating more recent data to enhance the accuracy of predictions. By monitoring and improving the models iteratively we can further enhance the projects capabilities.

In summary this project excels in its approach that includes data preprocessing, model training and evaluation. The chosen models. RandomForestRegressor and GradientBoostingRegressor. Have proven to be tools for predicting population values. They demonstrate adaptability and effectiveness. The detailed analysis along with aids provide valuable insights into population trends over time, for decision makers involved in urban planning.

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