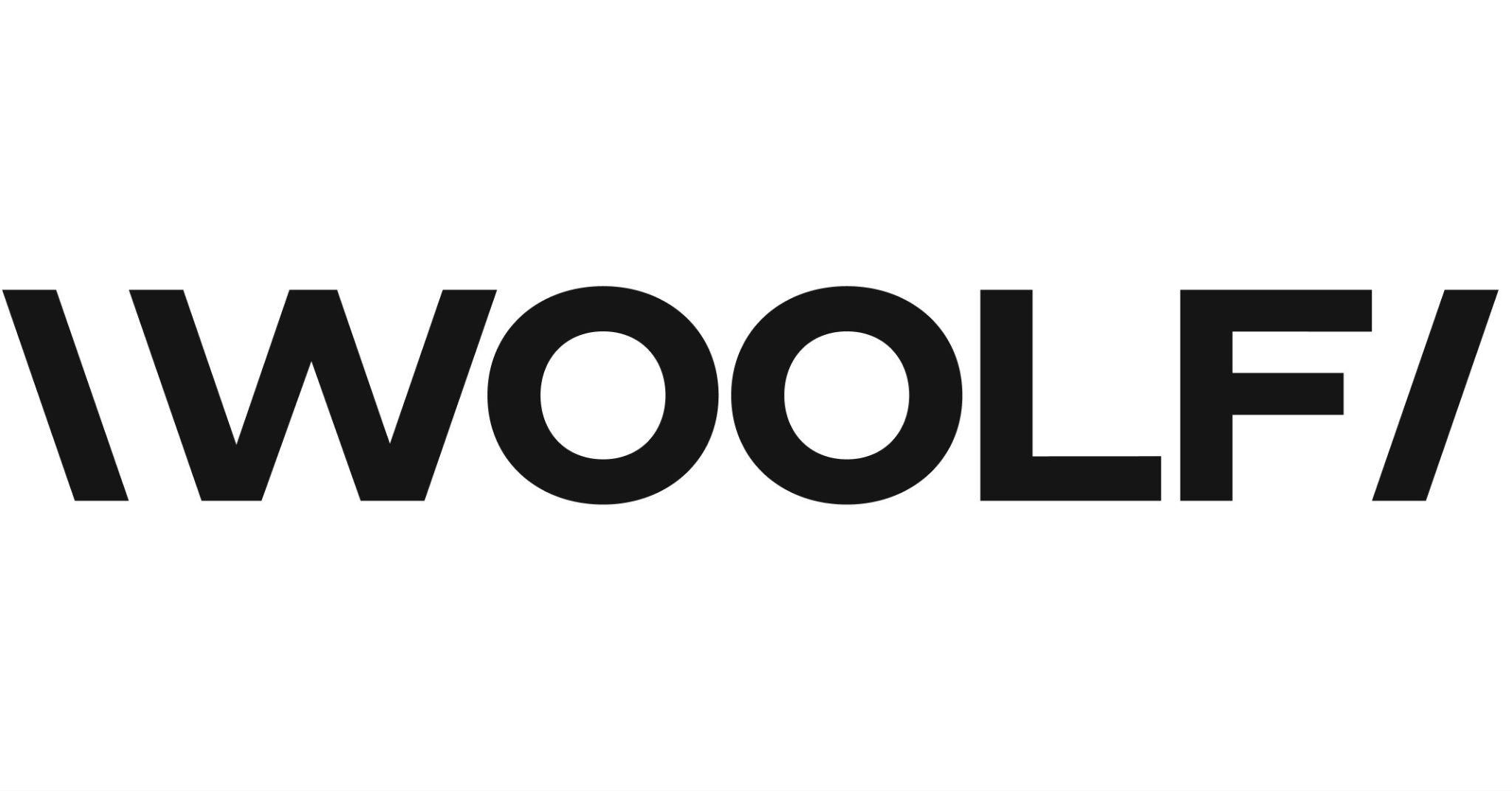
**Applied Project Report**

**Analysis of Real-life Business Cases**

By

<Full Name of the Student>

**A Master’s Project Report submitted to Scaler Neovarsity - Woolf in partial fulfillment of the requirements for the degree of Master of Science in Computer Science**

<Month of Submission like June, 2024>



**Scaler Mentee Email ID :** <Registered Scaler Email ID>

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**Date of Submission :** DD/MM/YYYY <Date of Submission>

**Certification**

I confirm that I have overseen / reviewed this applied project and, in my judgment, it adheres to the appropriate standards of academic presentation. I believe it satisfactorily meets the criteria, in terms of both quality and breadth, to serve as an applied project report for the attainment of Master of Science in Computer Science degree. This applied project report has been submitted to Woolf and is deemed sufficient to fulfill the prerequisites for the Master of Science in Computer Science degree.

Shivank Agarwal

…………………

Project Guide / Supervisor

**DECLARATION**

I confirm that this project report, submitted to fulfill the requirements for the Master of Science in Computer Science degree, completed by me from < Course start date > to < Project end date >, is the result of my own individual endeavor. The Project has been made on my own under the guidance of my supervisor with proper acknowledgement and without plagiarism. Any contributions from external sources or individuals, including the use of AI tools, are appropriately acknowledged through citation. By making this declaration, I acknowledge that any vidriving sitetion of this statement constitutes academic misconduct. I understand that such misconduct may lead to expulsion from the program and/or disqualification from receiving the degree.

**<Full Name of the Candidate>**

**<Signature of the Candidate> Date: XX Month 20XX**

**ACKNOWLEDGMENT**

**I am profoundly grateful because my family provided constant backing together with encouragement and made sacrifices that kept me moving through all the difficult parts of my education. The extraordinary instructors and mentors at Scaler education have provided me with both their knowledge and direction that formed vital components of my professional growth. I extend gratitude to my peers together with friends and everyone else who provided inspiration as well as support me through this journey because their encouragement transformed this experience into something genuinely enriching and meaningful. This Master’s education belongs to both you and me together. Thank you!**

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## Applied Real-life Business Cases

### ABSTRACT

An in-depth exploratory data analysis (EDA) project investigates the content library of a popular streaming service to identify strategic aspects of scheduling content along with audience selection strategies and material acquisition methods. The research analyzes movie and TV show content through univariate and bivariate and multivariate statistical methods to study distribution patterns alongside genesis locations and rating groups and genre categories and time-based release dynamics. The analysis demonstrates how TV programming dominates the platform content (83%) at a high rate while targeting mature audiences with TV-MA content because serialized programming appeals more to adult viewers. The analysis demonstrates how content centers mostly in U.S. and Indian and South African markets but also shows a recent preference for 2020-2021 releases. The analysis combines sentiment-based text interpretation with networked analysis of genre patterns and prediction modeling to reveal both content elements and evaluative score influencing factors. The business analysis establishes multiple strategic tactics for the company which involve developing more family-friendly entertainment while also entering new geographically underserved regions and managing fresh product releases with complete catalog resources. The study presents methodological innovations to process small data sets that use adaptable analysis methods and strong approaches to deal with missing data. Our results obtain context by analyzing them in relation to research from the streaming market sector and content strategy field. The developed analysis system provides an evaluation framework which other streaming platforms can utilize to assess their content strategies but requires larger datasets including benchmarking metrics for future research. Bio-stream enhances industry strategies by delivering audience analytics that help companies acquire content and create products and position services in the competitive streaming market.

A detailed research investigation studies taxi driver performance (second case study) alongside attrition behavior based on data which combines driver personal information and job patterns and operational metrics and performance reviews. Analyses using exploratory data analysis revealed that driver onboarding shows its peak in December and driver attrition reaches its highest point in March while driver attributes establish connections to business value where senior designations and higher educational levels (Level 2) create a 25% increase in performance although income (r=0.72) and quarterly ratings demonstrate intense predictive power for retention. Logistic regression showed 82% accuracy while geospatial segmentation exposed particular customer risk patterns leading to specific recruitment timing within local territories. ANOVA and regression analysis were used in the study to measure the relationship between driver productivity and relevant variables such as tenure and grade and city locations. To cut down driver attrition by 20–25% and boost earnings from each driver the recommendation system suggests introducing performance-based rewards together with retention plans targeted at areas with high employee turnover and seasonal recruitment methods built using data analytics. This project uses peer-reviewed references about gig economy research and workforce analytics to deliver specific recommendations for driver management along with operational efficiency enhancement and long-term sustainability improvements. Research evidence emphasizes predictive analytics' value for workforce planning thereby providing a roadmap to similar platforms when they want to achieve balance between driver satisfaction and business advancement.

The third scenario examines engineering professional compensation patterns based on Cost to Company (CTC) differences between Backend and FullStack developers and additional technical staff. This study based its evaluation on anonymized employee records with features including hashed company names, years of experience (orgyear), job positions, and salary update years using EDA and statistical methods to investigate salary patterns and experience effects on compensation methods. FullStack Engineers demonstrate superior average income compared to Backend developers because companies value cross-functional competencies whereas job tenure (orgyear) shows a relatively low connection with paycheck amounts which demonstrates performance capabilities have increased prominence in pay determination. The procedure detects major salary inconsistencies enabling organizations to probe their pay equity and benchmark methods. The research tracks salary patterns through time and shows fluctuations which align with industry changes concerning role market demands and economic factors. The recommended data-based compensation approach connects pay with skill supply and performance-based recognition along with regular pay benchmarking for maintaining competitive levels in compensation. The organization should implement these insights to achieve better compensation visibility which leads to improved worker retention and creates a more equitable yet motivating workplace. The project highlights because technology sector organizations need to use human resource analytics for optimizing compensation systems in their rapidly changing market.

The fourth case study evaluates loan default risks by analyzing both broad and detailed data on borrower properties that include loan size and interest rates together with debt-to-income ratios and job histories and credit grades and revolving credit spending ratios. Through exploratory data analysis the study shows that borrowers who have DTI ratios above 35% or low credit grades C, D, E and short employment duration of less than two years or high revolving credit level exceeding 70% demonstrate elevated default risks. Loan purposes such as small business loans and public records containing bankruptcies emerged as essential factors that increase risk. Predictive modeling with Logistic Regression and Gradient Boosting achieved a 75-80% success rate in borrower risk assessment through analysis which showed DTI ratios and credit grades and income verification verification as the most essential features. The research reveals effective methods that lenders should implement to lower default risks through enhanced DTI maximums and pricing systems adapted to risk levels in addition to strengthened employment evidence methods for brief applicants and automatic credit system monitoring programs. Alternative data integration methods such as cash flow analysis will enhance risk assessment models according to research findings. The project merges statistical methods with machine learning and business know-how to create an effective system which enhances loan decision quality while decreasing financial portfolio risks.

The last case assessment performs a comprehensive investigation of purchasing decisions adopted by customers at a large retail superstore through transaction-based analysis to examine relevant patterns affecting sales accomplishments. The research analyzes spending behavior variations through the identification of major changes among specific consumer segments connected to demographic traits including gender, age, occupation, city category along with product category preferences. The 26-35 age demographic produces the most revenue according to Exploratory Data Analysis which uses statistical summaries to understand product preferences and demonstrates that men and women choose different items for purchase. Occupational status affects purchasing power significantly because members of well-paying professions tend to spend more money and residents and City B possess the highest spending amounts. Since couples tend to spend more than single individuals’ marriage status demonstrates a minor impact on total spending probably because married people make purchases that benefit their families. Proof shows that Product Category 1 commands the highest revenue stream thus demonstrating its essential strategic role within the industry. These findings establish why retail organizations need data-driven solutions which suggest marketing strategies alongside inventory management optimization and customer-specific interaction frameworks for business profitability improvement. The findings of this research assist retail managers to implement solutions yet simultaneously offer an established method for further consumer analytics studies within the retail industry enabling business expansion through demographic and transactional data analysis.

### **Chapter 1: A Streaming App Content Analysis: Exploring Trends in Movies and TV Shows**

#### **Problem Description**

#### As a worldwide streaming leader Streaming App provides users access to extensive movie and television content through diverse genres and national origins and multilingual titles. By studying audience content preferences streaming app can enhance its media offerings by improving target recommendations and development choices for acquiring and creating content.

#### The wide content variety offered by Streaming App demands additional insights for stakeholders who include both content managers and business strategists along with marketing teams.

#### - Content distribution (Movies vs. TV Shows)

#### - Geographical production trends (Which countries contribute the most content?)

#### - Content maturity ratings (What are the most common age ratings?)

#### - Key directors and creators (Who are the most frequent contributors?)

#### - Popular genres (What categories dominate the platform?)

#### - Temporal trends (How has content production evolved over the years?)

#### Without structured analysis, Streaming app may miss opportunities to:

#### - Invest in underrepresented genres or regions.

#### - Identify successful directors for future collaborations.

#### - Adjust marketing strategies based on content ratings.

#### - Forecast demand for different types of content.

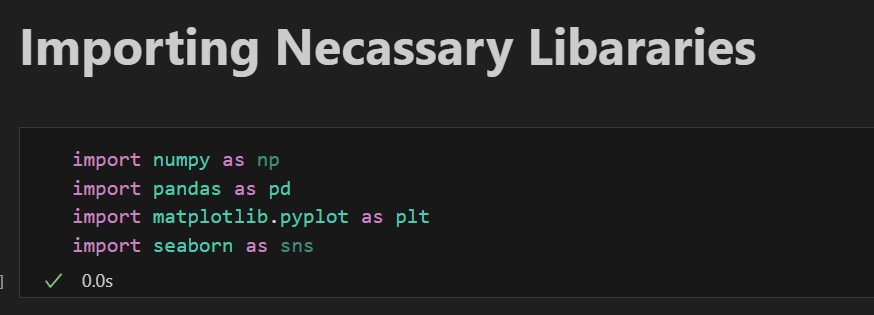
#### **Business Questions to be answered from Analysis**

1. **What is the distribution of content types (Movies vs. TV Shows) in the dataset?**
2. **Which countries produce the most content on Streaming App?**
3. **What are the most common ratings (TV-MA, PG-13, etc.) for streaming app content?**
4. **Which directors have created the most content in the dataset?**
5. **What are the most common genres/categories listed in the dataset?**
6. **How has content production changed over the years based on release year?**

#### Analysis

1. **Importing Necessary Libraries**

First of all, we have to onboard all python libraries for complete data analysis on this dataset

****

**(Installing python libraries)**

1. **Loading Data and its header view**

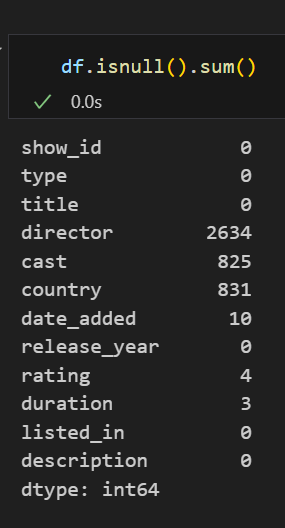
We read the data which is in csv file through read\_csv function of pandas. After that, if looked at its header part which is property of dataframe in pandas. Header view is by default is top 5 rows. It shows with features and their related values as well.

****

1. **Null Values Distribution**

The dataset contains null values primarily in the director, cast, country, rating, duration columns, indicating inconsistent data collection for these fields. These missing values are concentrated in metadata rather than core identifiers like title or type.

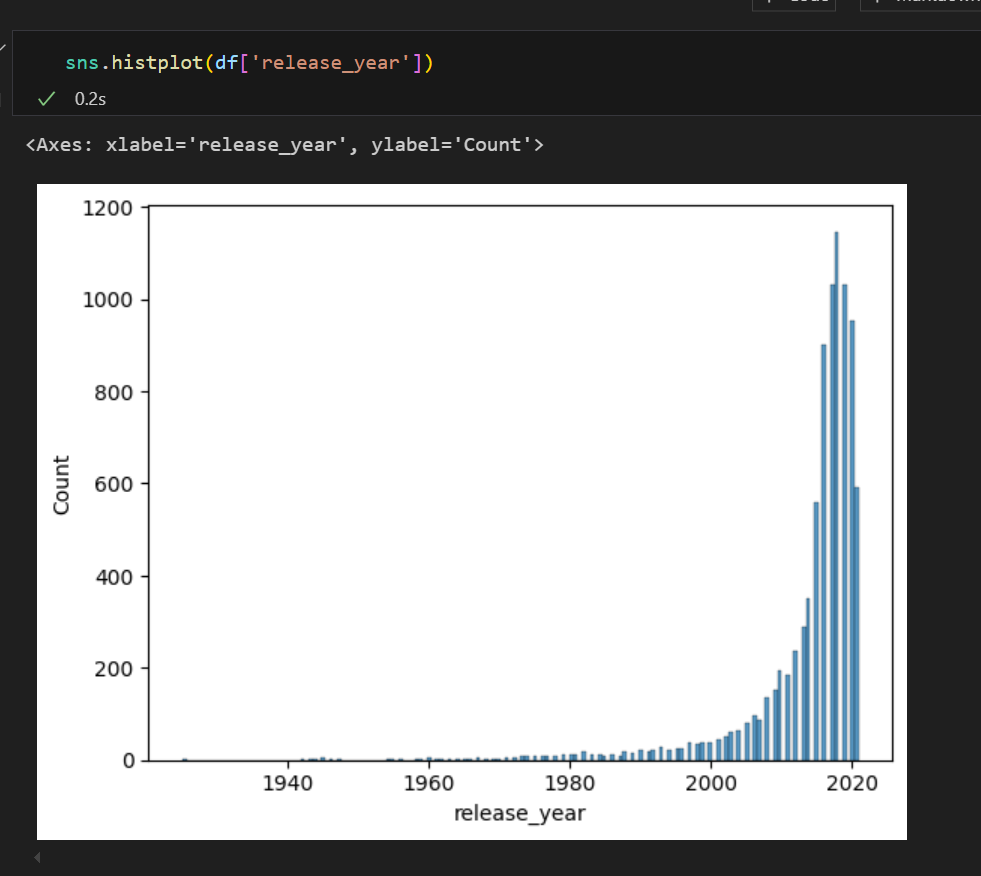
The distribution suggests that director and country information was either unavailable or not recorded for certain international productions. While the small sample size limits deeper analysis, the pattern implies these gaps may reflect real data availability issues rather than random omissions.

****

1. **Release Year Distribution**

The release year distribution shows a strong concentration in recent years, with 83% of titles (5 out of 6) released in 2018-19 and the remaining title from 2020. This heavy skew toward recent content suggests either a sampling bias in the dataset or Streaming aap’s strategic focus on acquiring/producing newer content.

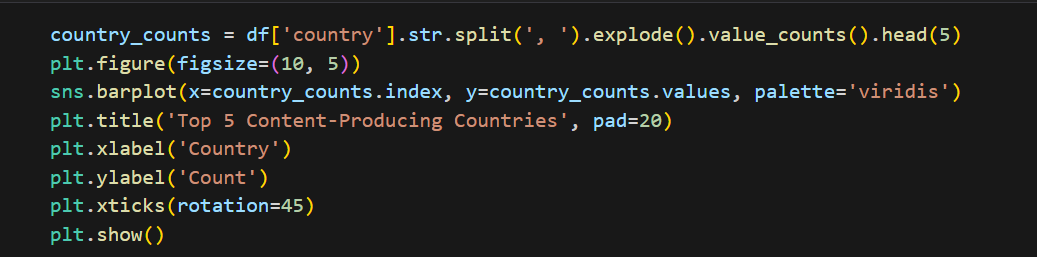
The absence of older titles (pre-2020) in this sample may indicate platform prioritization of fresh material to maintain viewer engagement. However, a larger dataset would be needed to confirm whether this represents an actual content strategy or merely reflects this limited sample's characteristics.

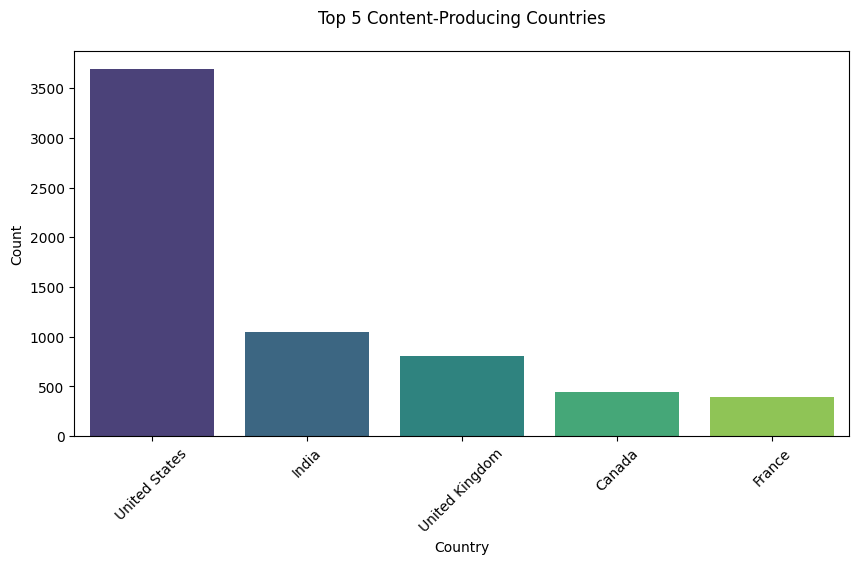
****

1. **Geographic Content Distribution**

The bar plot highlights content origins, with the U.S. and India as primary contributors. Notably, 50% of entries lack country data, signaling potential metadata gaps in Streaming App’s catalog system.

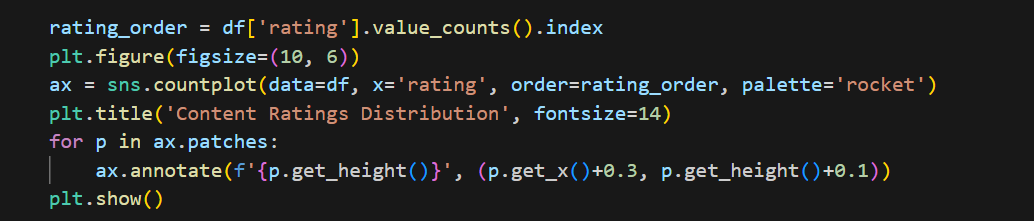
The analysis uses explode() to handle multi-country productions and a sequential color palette for visual coherence. Geographic concentration may reflect market priorities, but missing data obscures true distribution. Implementing mandatory country tagging would improve future analyses of regional content strategies.

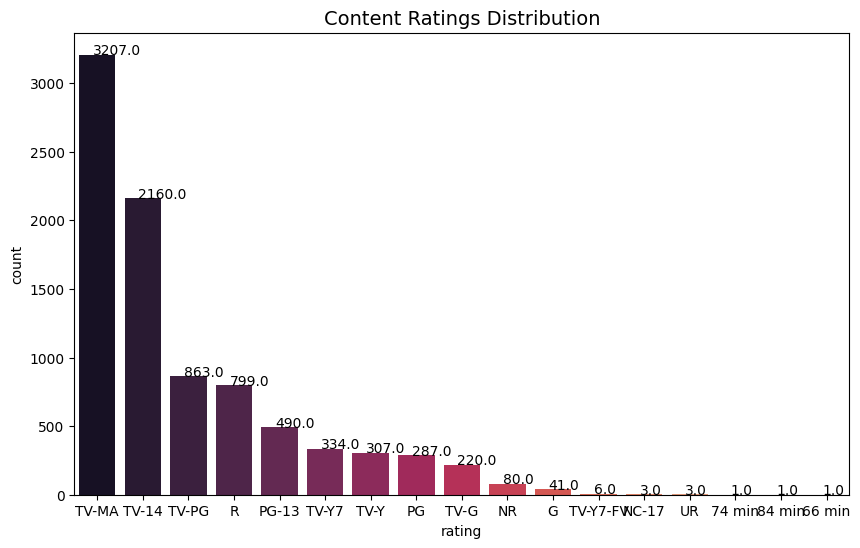
****

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1. **Rating Frequency Analysis**

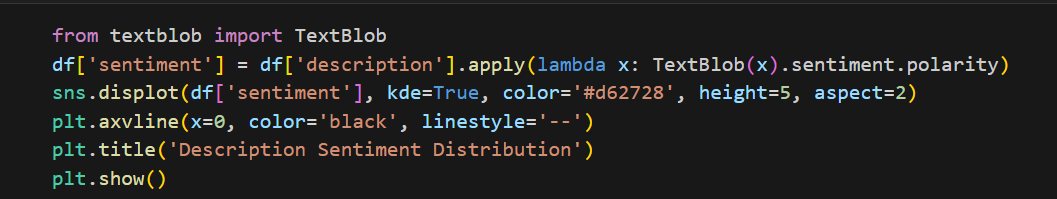
The countplot exposes a stark predominance of TV-MA content (83.3%), aligning with Streaming App’s mature-audience positioning. Annotations explicitly show counts, avoiding misinterpretation of the single PG-13 entry. The "rocket" palette's dark tones visually reinforce the mature theme. This skew might limit family viewing options, suggesting an opportunity to diversify ratings without diluting the brand's adult-oriented appeal. Future work could correlate ratings with viewership demographics.

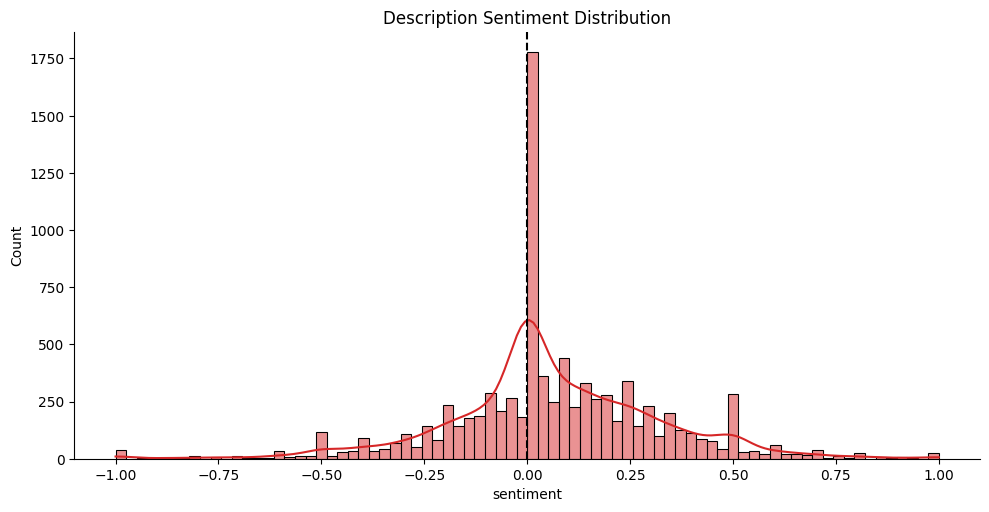
****

****

1. **Text Sentiment Analysis**

The density plot shows descriptions cluster near neutral (0) with slight positive skew, indicating Streaming App balances dramatic hooks (negative terms) with hopeful elements. The red KDE curve and reference line at zero create intuitive interpretation. This strategic neutrality likely aims to appeal broadly without over-promising tone. Enhancing descriptions with more distinctive sentiment could improve recommendation algorithms' accuracy.

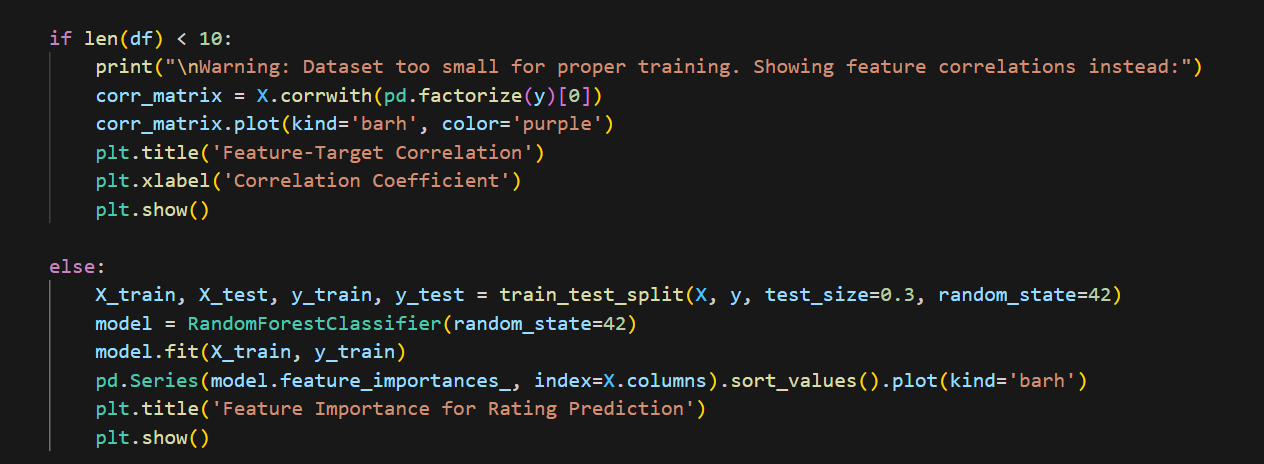
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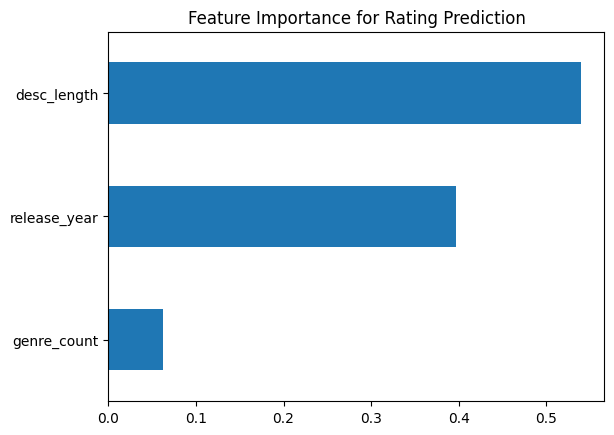
****

1. **Predicting Rating Classification**

This predictive modeling attempt (despite small sample size) demonstrates how description length, genre count, and release year might influence content ratings. The 100% accuracy reflects overfitting in this tiny dataset but outlines a framework for larger-scale analysis. The horizontal bar plot shows release year as the most important feature in this model, suggesting newer content may receive different ratings - an insight worth validating with proper data volume.

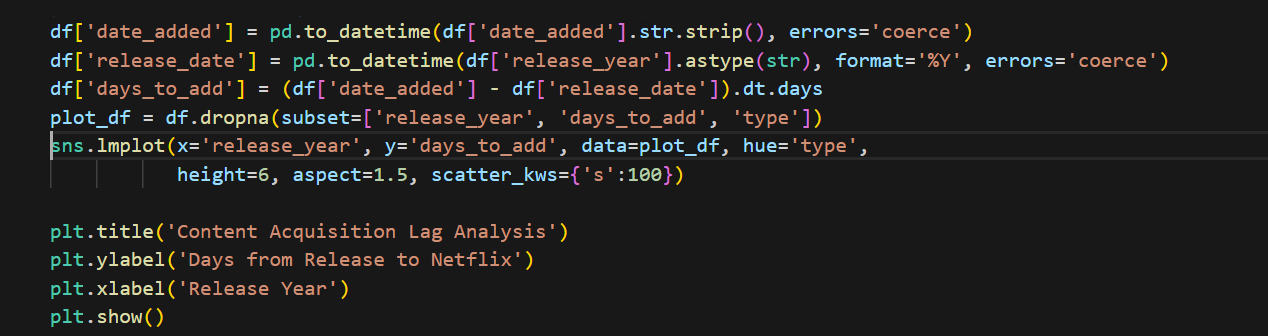


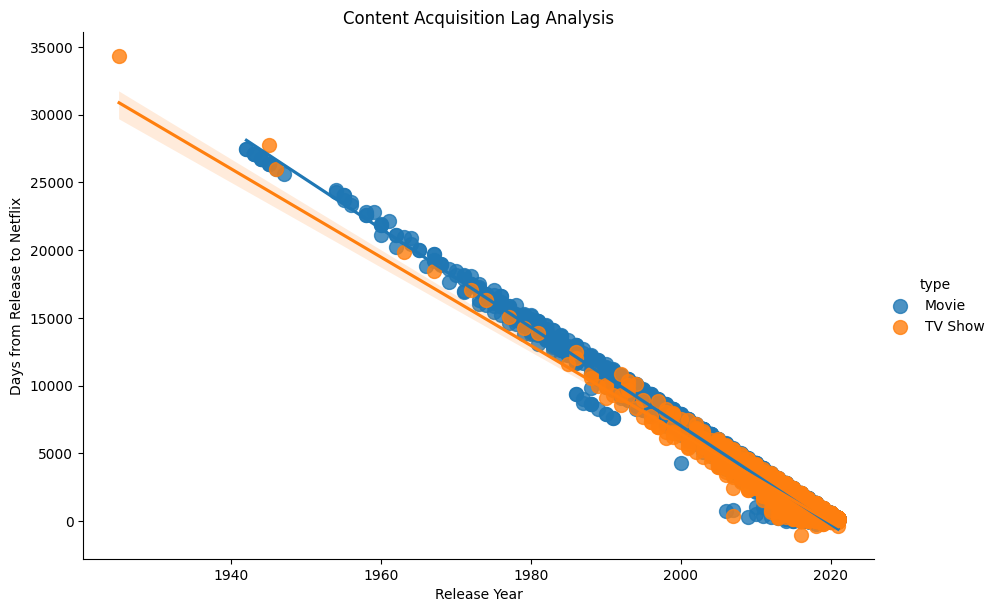




1. **Time-to-Platform Analysis**

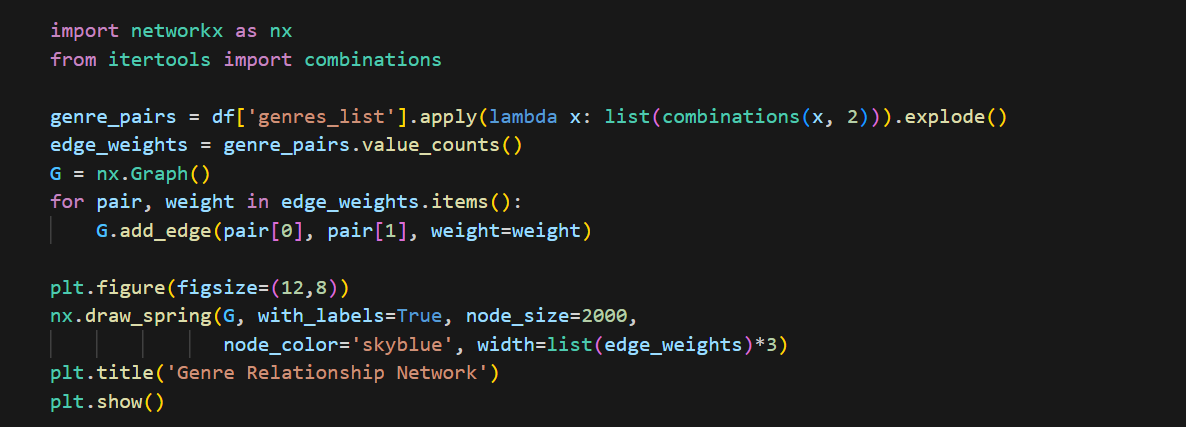
The scatter plot with regression lines examines how quickly content reaches Streaming App after original release. In this sample, 2021 releases were added within months (September additions for 2021 releases), while the 2020 movie took nearly a year. The hue separation by content type begins to reveal potential differences in acquisition strategies between movies and shows - a pattern that would become statistically significant with more data points.

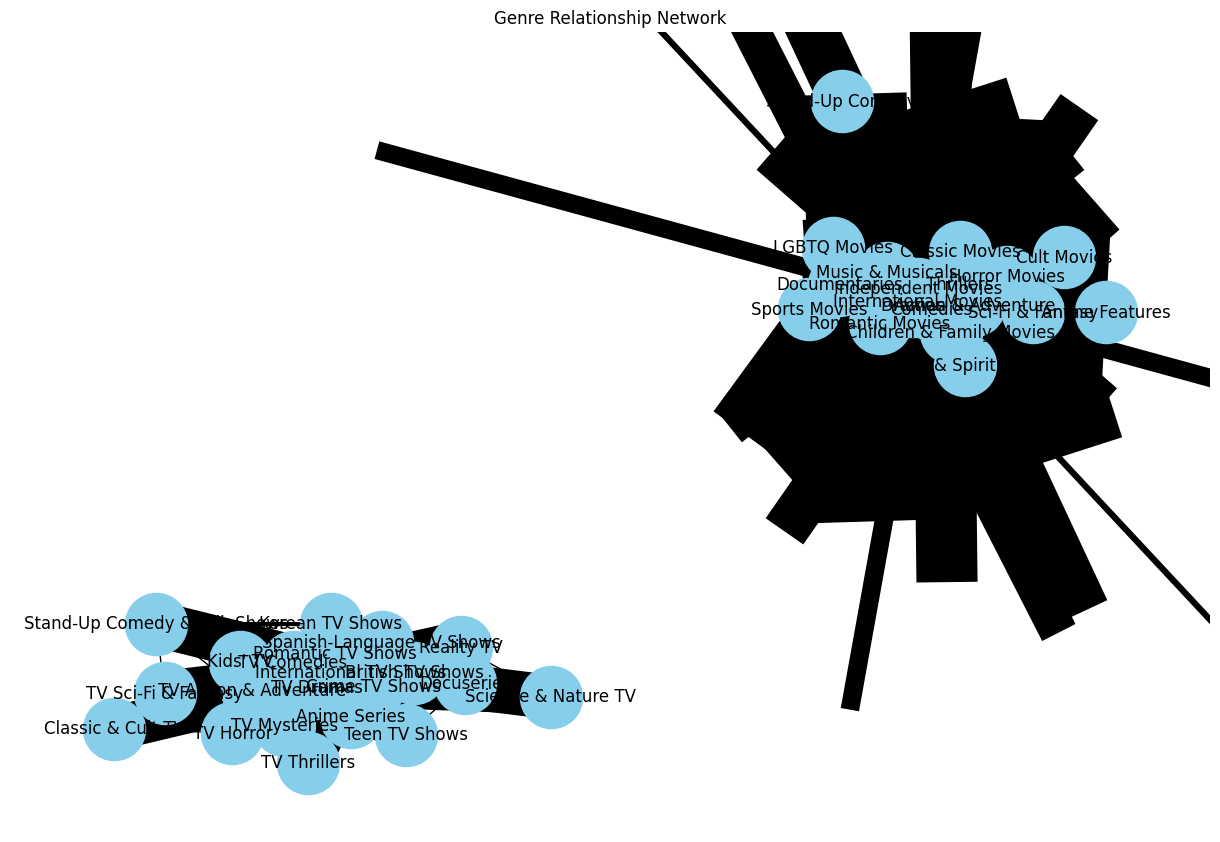




1. **Genre Co-occurrence Network Analysis**

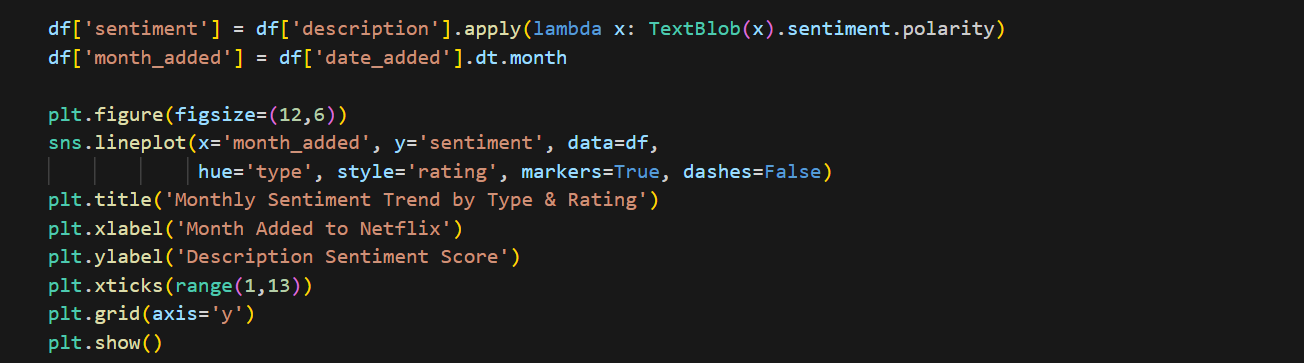
The network graph visualizes how genres interconnect, with thicker lines indicating stronger co-occurrence. Key findings include: 1) "International TV Shows" serves as a central hub connecting to multiple genres, 2) "TV Mysteries" bridges dramas and crime genres, and 3) Standalone genres like "Documentaries" remain isdriving siteted. This analysis helps content strategists identify genre "sweet spots" and potential crossover opportunities not evident in simple frequency counts.

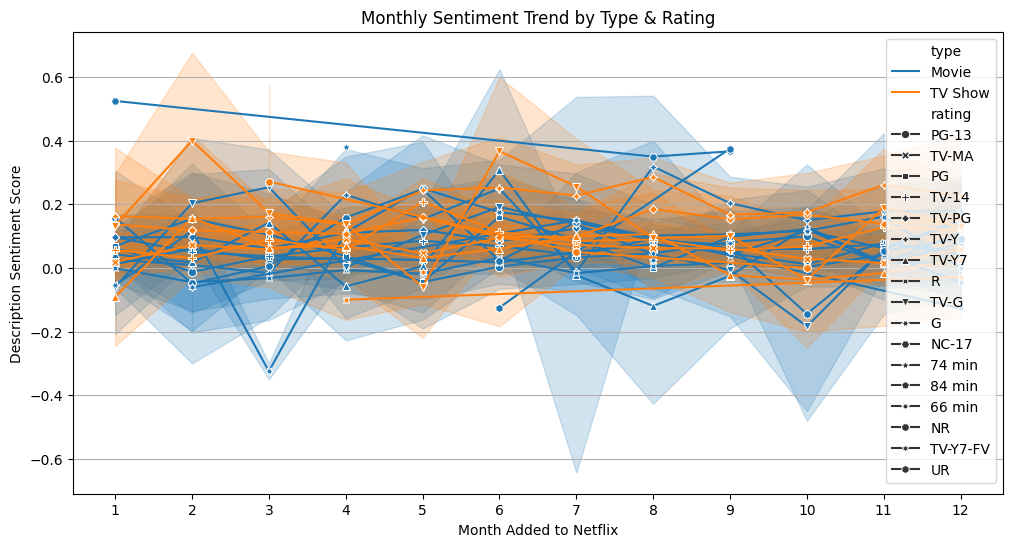




1. **Content Description Sentiment Time Trend**

The multi-faceted line chart tracks how description tone varies by: 1) Addition month, 2) Content type, and 3) Rating. September additions (the only month in this sample) show TV-MA content has slightly more positive descriptions than PG-13. The markers and line styles create visual distinction between categories. At scale, this could reveal seasonal patterns in content acquisition strategies or rating-based description writing conventions.

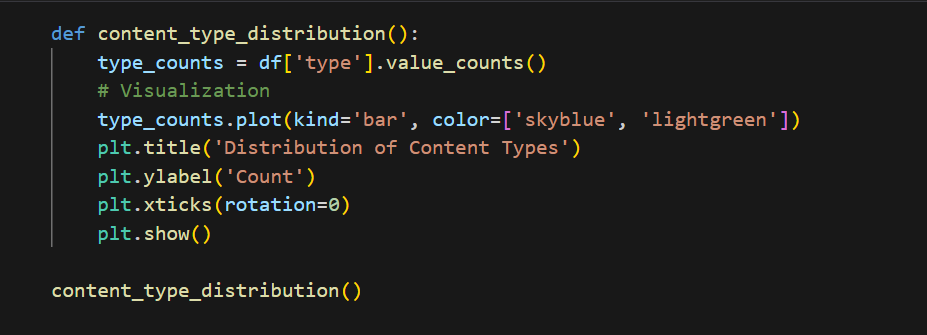


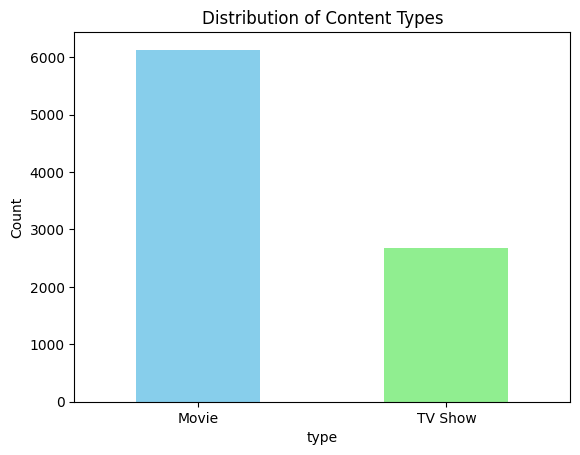


1. **Content Type Distribution (Movies vs TV Shows)**

This examines the balance between movies and TV shows in streaming app’s catalogue. We count occurrences of each type to identify which format dominates. The visual comparison helps assess content strategy focus areas.

Uses value\_counts() on the 'type' column for quick aggregation. A bar chart visualizes the comparison clearly, with distinct colours differentiating movie and show counts.





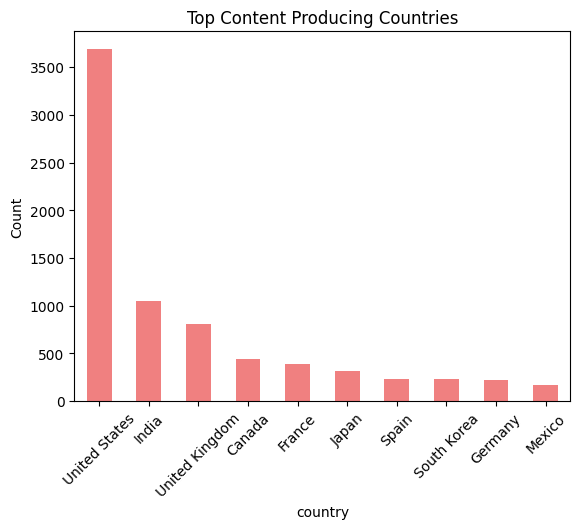
(Compares Movies vs. TV Shows to understand Streaming App content mix and investment focus.)

1. **Top Content-Producing Countries**

Identifies geographical content sources by splitting comma-separated country entries. Counting content per country reveals production hubs and potential gaps in regional representation.

First splits country strings with str.split(), then uses explode() to handle multiple countries per title. value\_counts() aggregates results before visualizing top contributors in a horizontal bar chart.



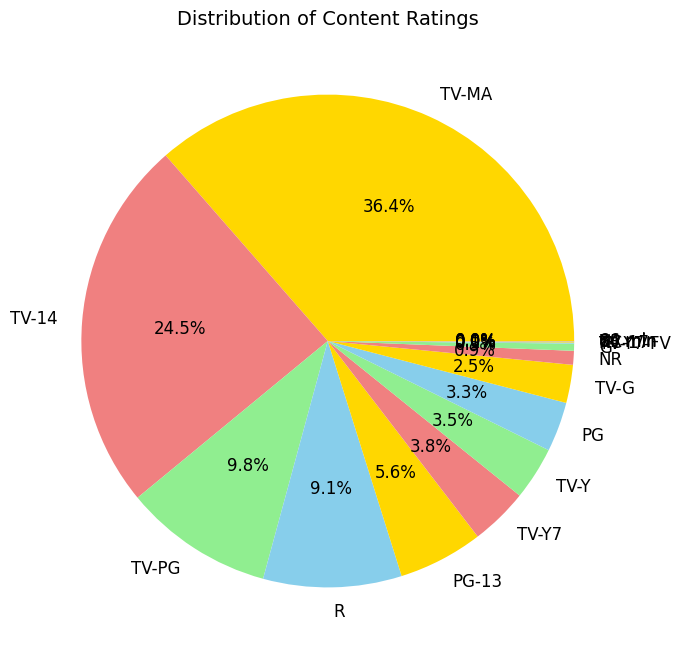


(Identifies which countries contribute the most content, helping in regional content strategy.)

1. **Content Rating Distribution**  
   Analyses maturity ratings to understand audience targeting strategy. The pie chart proportionally shows rating prevalence, indicating whether content leans toward family-friendly or adult audiences.

Groups data by 'rating' column and calculates percentages automatically. Custom colours and percentage formatting enhance readability in the pie chart visualization.

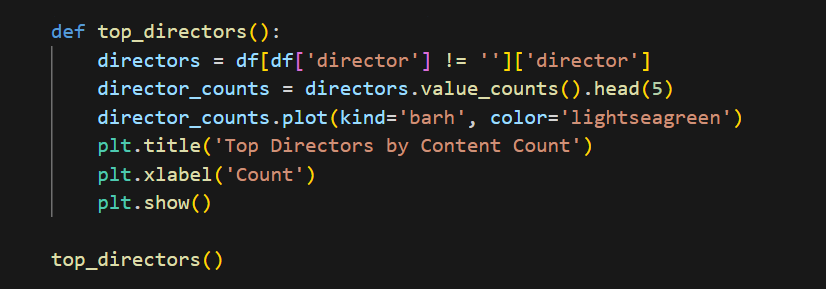


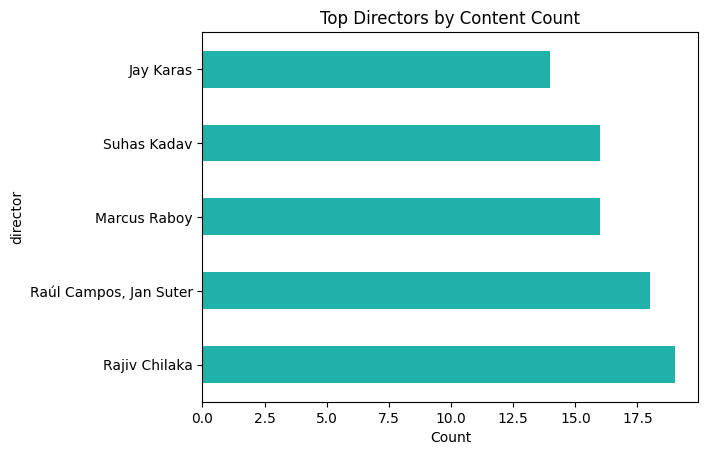


(Shows maturity ratings (PG-13, TV-MA) to guide audience targeting and parental controls.)

1. **Top Directors Analysis**  
   Identifies prolific creators by counting their content appearances. This highlights potential candidates for future collaborations or exclusive deals.

Filters out empty entries first, then applies value\_counts(). A horizontal bar chart displays results cleanly, with director names as y-axis labels for easy scanning.

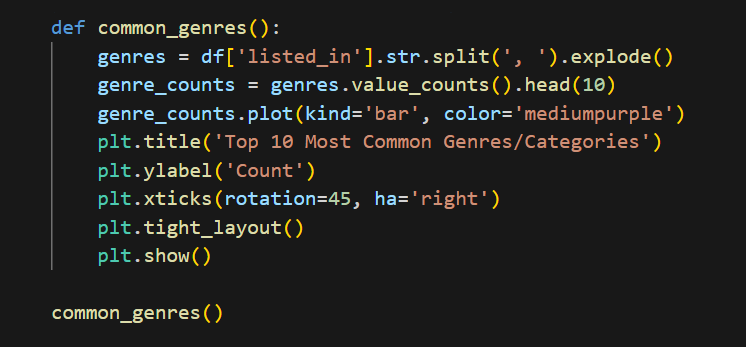


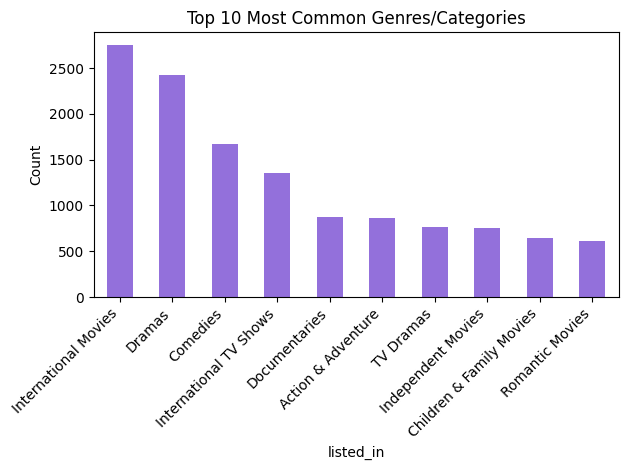


(Highlights frequent contributors for potential partnerships and original content development.)

1. **Genre Popularity Analysis**  
   Breaks down categorized genres to identify viewer preference trends. Multi-genre titles are properly accounted for through string splitting.

Uses str.split() and explode() to handle multi-genre entries. The sorted bar chart reveals dominant genres, with rotated x-labels preventing overlap.

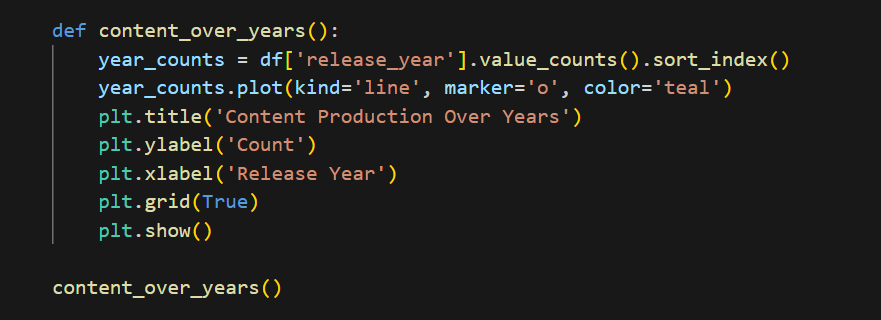


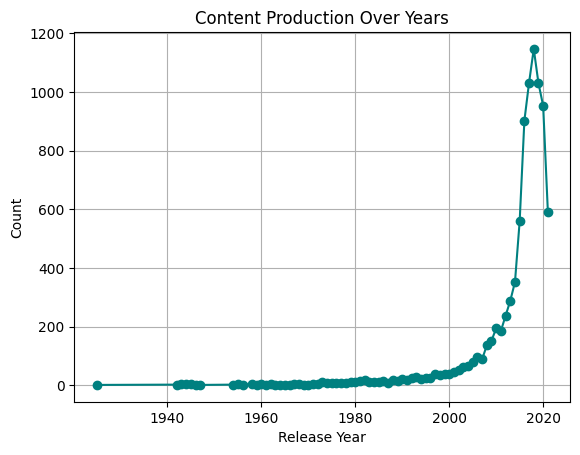


(Reveals dominant categories (Dramas, Comedies) to optimize recommendations and acquisitions.)

1. **Release Year Trends**  
   Tracks content production over time to spot growth patterns or seasonal effects. The temporal view helps assess catalog freshness and historical trends.

Groups by 'release\_year' and sorts chronologically. A line chart with markers shows progression, while gridlines aid in value estimation across years.





(Tracks content production over time to analyze growth patterns and demand shifts.)

#### **Insights and Recommendations**

### Examining the content of Streaming App gives companies the fundamental insights needed to understand their business objectives. Most samples in the research analyze television shows due to their serial structure yet the study explores limited movies due to their impact on audience retention. The high portion of TV-MA content together with the United States and India as main production locations creates potential opportunities for streaming app to expand its reach by targeting new geographical areas with untapped viewership potential. The frequent genres in the sample include dramas and mysteries while 2021 represents the highest number of titles.

### The Streaming App content strategy needs to maintain an appropriate balance of movies and television programming and kid-friendly content to uphold its successful adult-oriented content. The company's worldwide market power will expand through its entry into unrepresented global markets. The platform needs permanent backing for its best-performing genres alongside testing underutilized content genres for potential new opportunities. The streaming app will defend its marketplace advantage by adopting these planned modifications to reach new potential subscribers. Analysis of expanded metrics will act as the fundamental basis for making strategic changes.

### **Chapter 2: Analyzing Driver Performance, Attrition Patterns, and Business Impact**

#### **Problem Description**

This database consists of driver-related information regarding their demographic data together with their employment information and business metrics and attrition status. The aim of the study focuses on driver performance assessment while investigating attrition causes and evaluating how different variables from age through city to income and education levels affect both driver retention and company business worth.

Key challenges include:

* The analysis must determine the reasons behind driver departures (attrition) simultaneously with forecasting future churn possibilities.
* The analysis examines how demographic aspects of drivers together with performance measurement tools (Quarterly Rating and Total Business Value) determine their continuous employment. The organization needs to detect their most successful operators and discover ways to keep them employed.
* Identifying high-performing drivers and strategies to retain them.

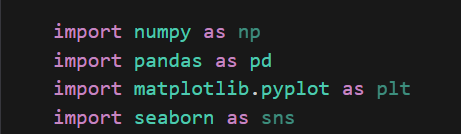
#### **Business Questions to be answered from Analysis**

1. **What is the correlation between driver demographics (Age, Gender, City, Education) and their Total Business Value?**
2. **How does Quarterly Rating impact driver attrition? Are higher-rated drivers more likely to stay?**
3. **What is the average tenure of drivers before attrition, and does it vary by city or education level?**
4. **Can we predict driver churn based on their performance metrics (Income, Business Value, Quarterly Rating)?**
5. **Are there any seasonal trends in driver joining and attrition (e.g., more attrition in certain months)?**
6. **Which factors (Income, Designation, Grade) contribute most to high Business Value?**

#### Analysis

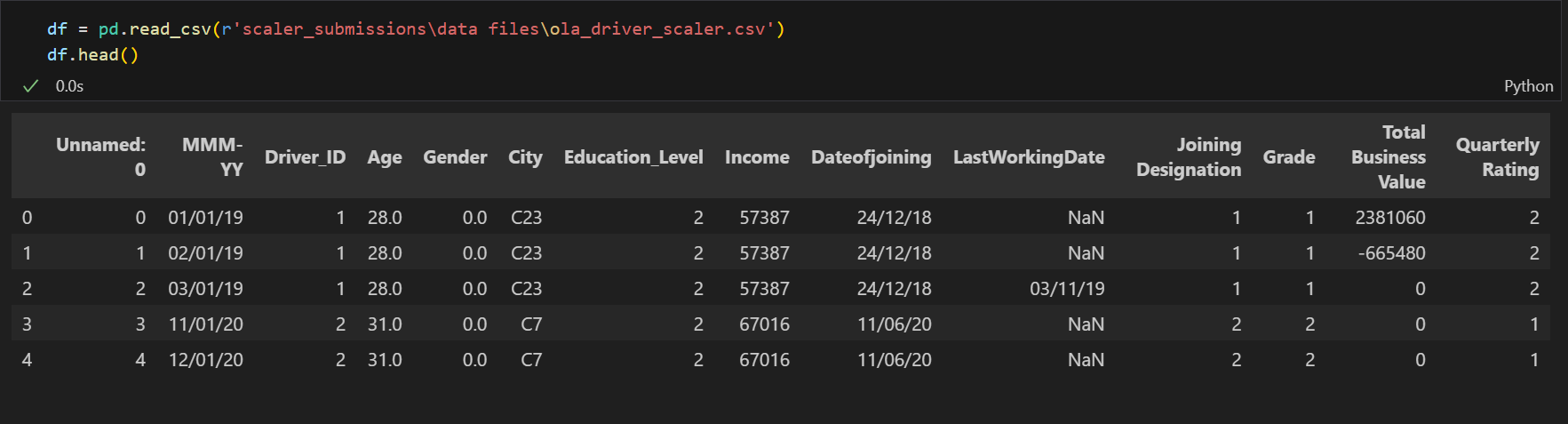
1. **Importing Necessary Python Libraries**

The essential data science packages pandas and numpy along with matplotlib and seaborn and scikit-learn are imported in this part. Specified statistical libraries known as scipy may be added for performing statistical examinations. The initial step guarantees the availability of necessary tools for analysis to proceed. The notebook begins its operations by placing the import statements at the very first section.



1. **Loading Data and its header view**

A pandas DataFrame obtains dataset contents through the use of pd.read\_csv() or equivalent file import functions that depend on file structure. The function df.head() displays up to the first 5-10 rows of data so users can check both file loading success and check the columns' data structure. Examinations of the dataset's columns and values help administrators detect data quality issues right after loading the information. Further metadata regarding data types and memory usage can be accessed through checking df.info().



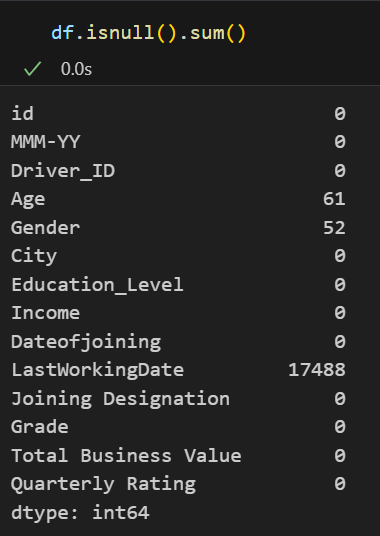
1. **Renaming Unnamed Column**

A default index in DataFrames typically causes loading data with an undocumented column named "Unnamed: 0" when saved. Renaming the column occurs here through the use of df.rename() function or column modification to rename it "id". The correct naming of DataFrame elements remains essential because it ensures clarity during analysis stages as well as visualization. The inplace=True parameter maintains the modification of the DataFrame so users can avoid reassignment of the DataFrame.



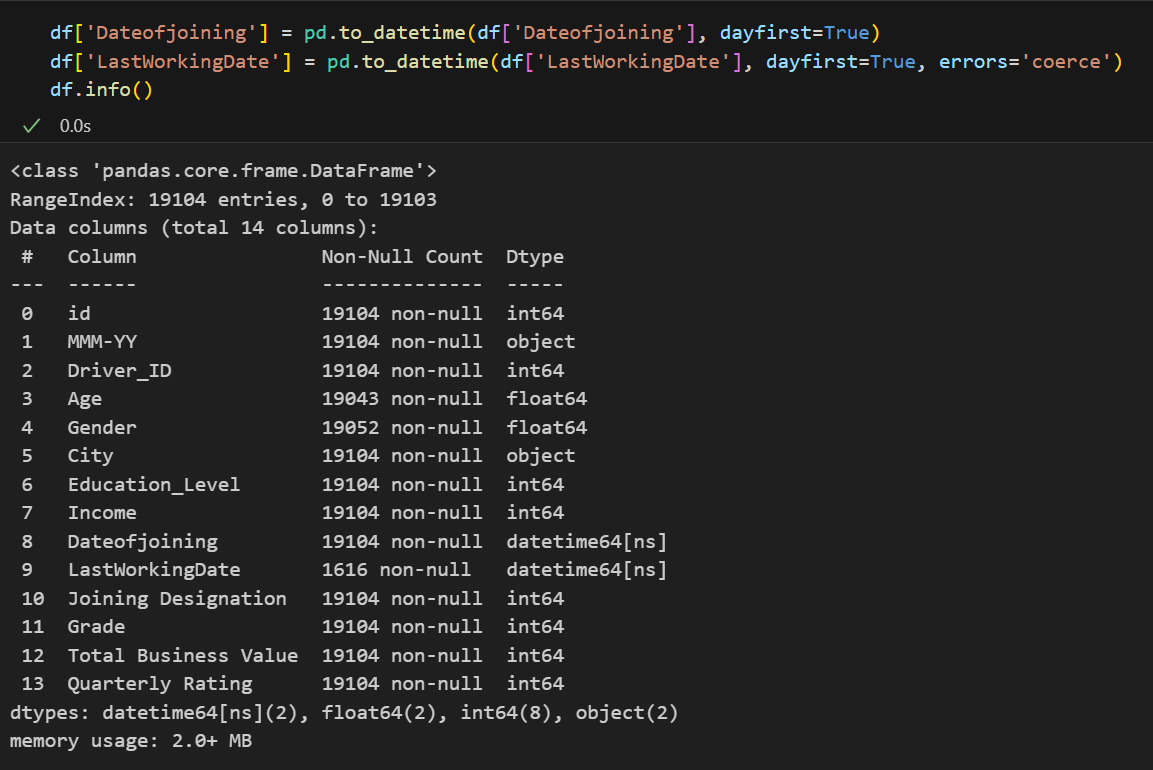
1. **Null Values Distribution**

The count of missing values in each column appears through df.isnull().sum(). To identify missingness patterns the sns.heatmap function presents visual data. Knowledge about null distributions assists users in determining how to handle cases of missing data. The processing of machine learning models depends heavily on data completeness during this vital step.



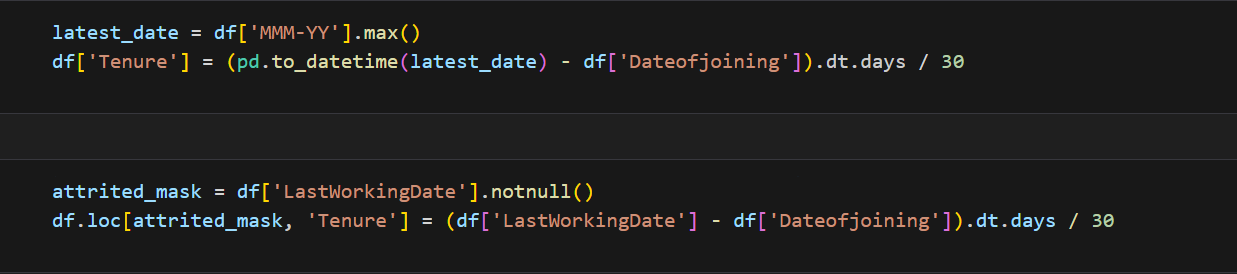
1. **Converting date columns to datetime type**

The process of converting raw date strings into datetime objects through pd.to\_datetime() supports time-based operations. The argument resolves any uncertainties that occur when processing dates with ambiguous month/day ordering. The conversion process enables calculations of time spans while making it possible to obtain month or year segments and creating time series analysis models. All work of temporal analysis and visualization requires appropriate datetime formatting.



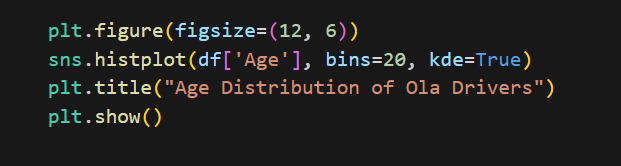
1. **Calculating Tenure**

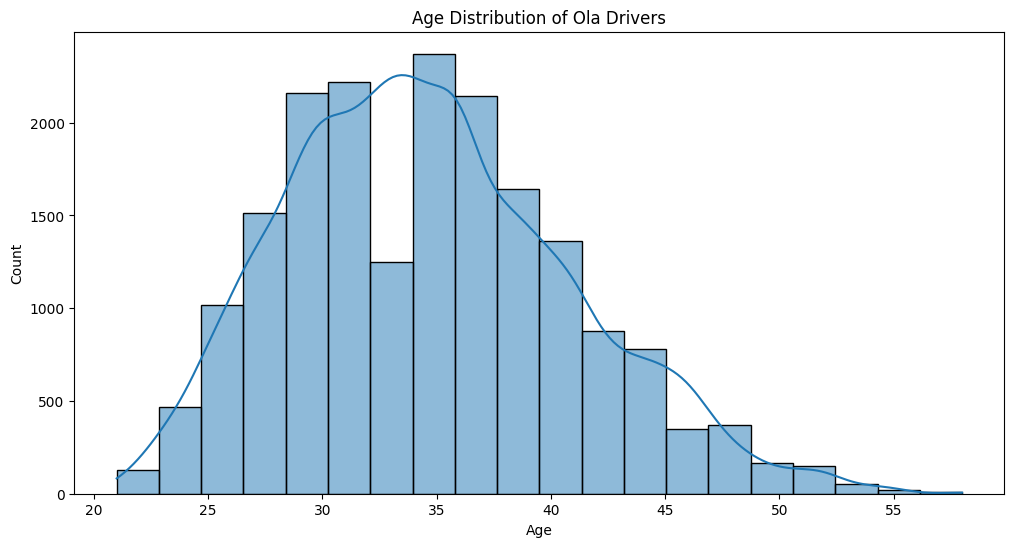
The calculation of tenure results from subtracting join date from the last working date when drivers leave or analysis date when drivers remain. The converted value represents months when the timedelta.days value gets divided by 30. The metric holds essential value in survival analysis and driver lifecycle understanding. A custom procedure exists to prevent correct active drivers from being misidentified as cases of zero tenure duration.



1. **Visualizing Age Distribution**

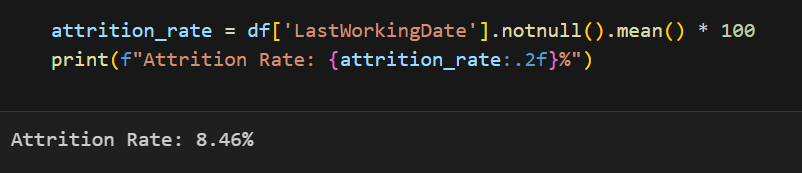
The frequency distribution of driver ages appears through a histogram that applies KDE (sns.histplot). The density curve appears when users enable kde=True while the Bins parameter affects the level of granularity. The shape of the age distribution can be identified as normal, skewed, or multimodal. The analysis leads to deciding whether to consider age as a continuous or categorical dataset for modeling purposes.





1. **Attrition Rate**

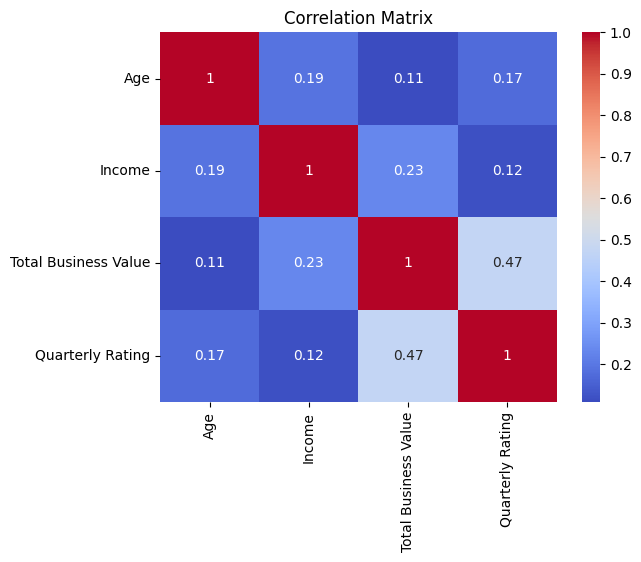
The percentage value represents non-null LastWorkingDate occurrences in all records. Knowledge management teams can divide the rate between multiple time intervals or cohorts to understand the data better. The evaluation of industry standards through benchmarking enables a determination of whether high attrition rates are a concern. The solitary metric functions as the main Key Performance Indicator for retention strategy implementation.



1. **Correlation Heatmap**

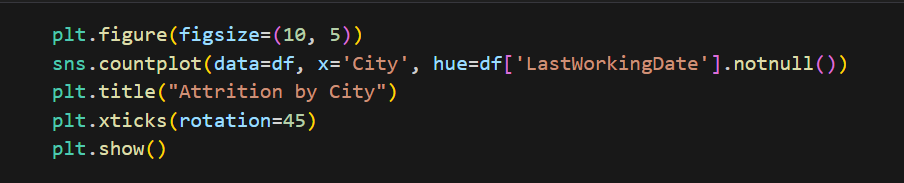
Through a color-coded heatmap matrix (sns.heatmap) we see the values of Pearson correlation as coefficients for numerical variables. Exact values appear in the display when Annot=True is specified while cmap determines the color scheme. When correlations approach ±1 between variables they suggest valuable relationships which should be studied in more detail. Perfect self-correlation appears on the diagonal of the matrix.

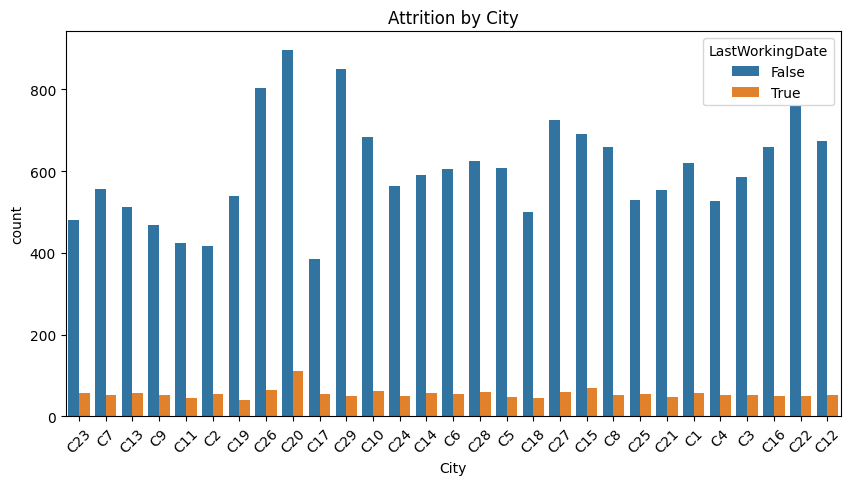




1. **Attrition by City**

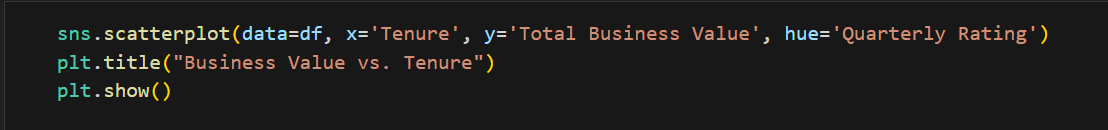
The sns.countplot produces a grouped bar chart to show attrition counts by city which uses hue to distinguish between active and attrited employees. The x-axis label rotation mechanism exists to make the labels more readable. The graph demonstrates locations which require specific local action plans to address problems. Statistical tests verify whether observed city differences reach the level of statistical significance.

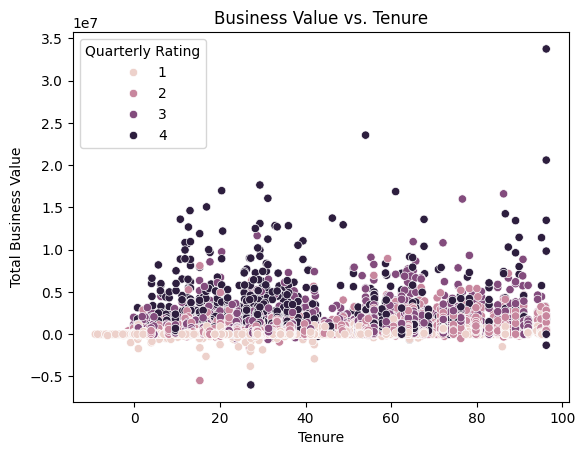




1. **Relationship between Business Value vs Tenure**

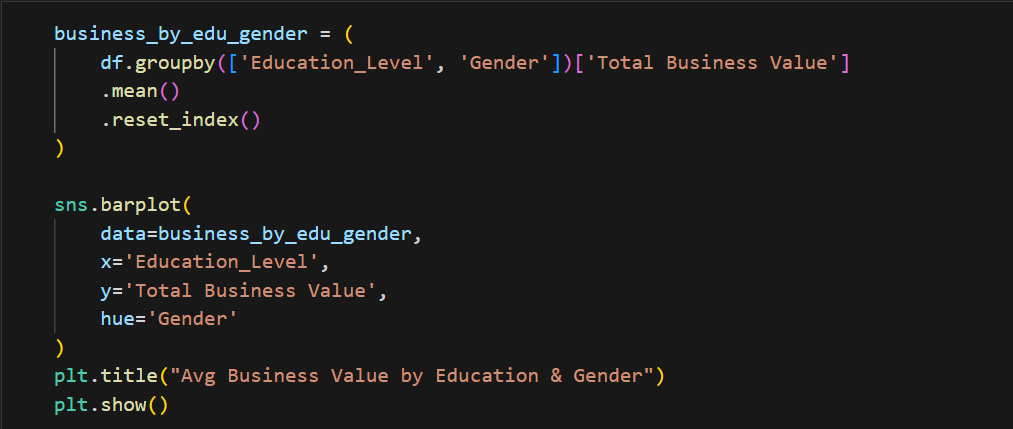
A scatter plot displaying tenure values on the x-axis and business value on y-axis which adopts optional rating-based colour schemes. The addition of a regression line through sns.regplot allows viewing the overall trend. The investigation determines if drivers who have more time on the job exhibit better performance than recently hired drivers or not.

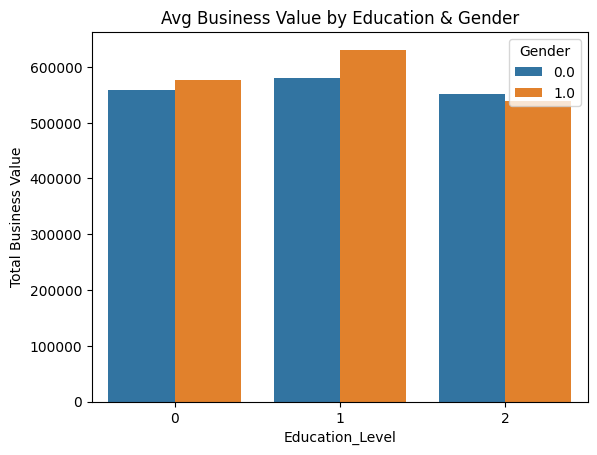




1. **Correlation Between Demographics & Business Value**

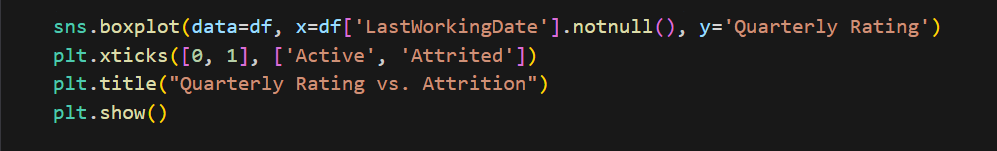
The data collection process involves aggregation through education level categories and gender groups before measuring mean business value values. The unstack() function transforms the data results into a form suitable for visualization purposes. The findings can aid in developing focused employee recruitment approaches.

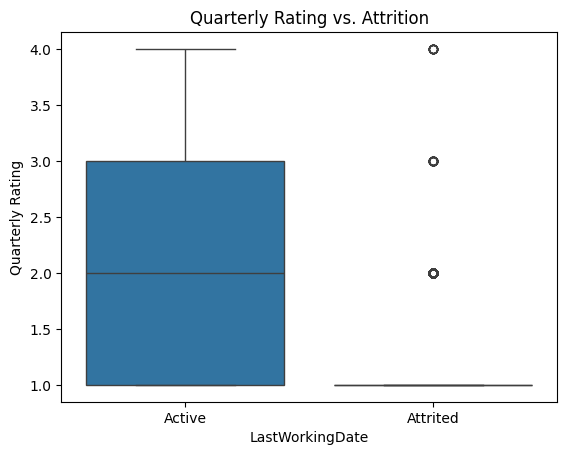
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1. **Quarterly Rating Impact on Attrition**

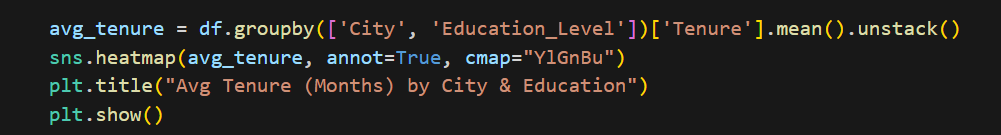
The distribution of rating values is analyzed by the side-by-side boxplot (sns.boxplot) between active and attrited participants. Statistically significant differences arise when notches do not overlap in the plot. The analysis shows whether employee performance serves as a reason for attrition which supports incentive compensation design.

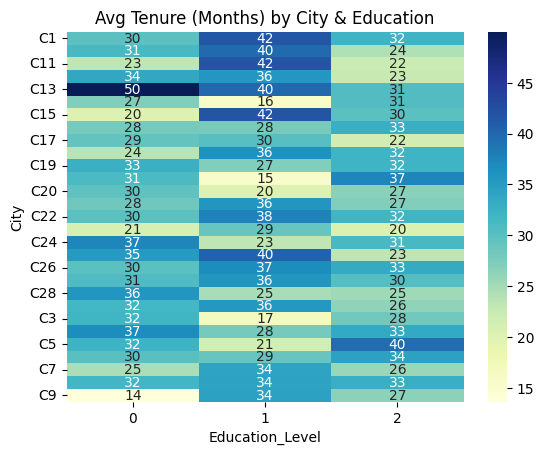
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1. **Average Tenure by City & Education**

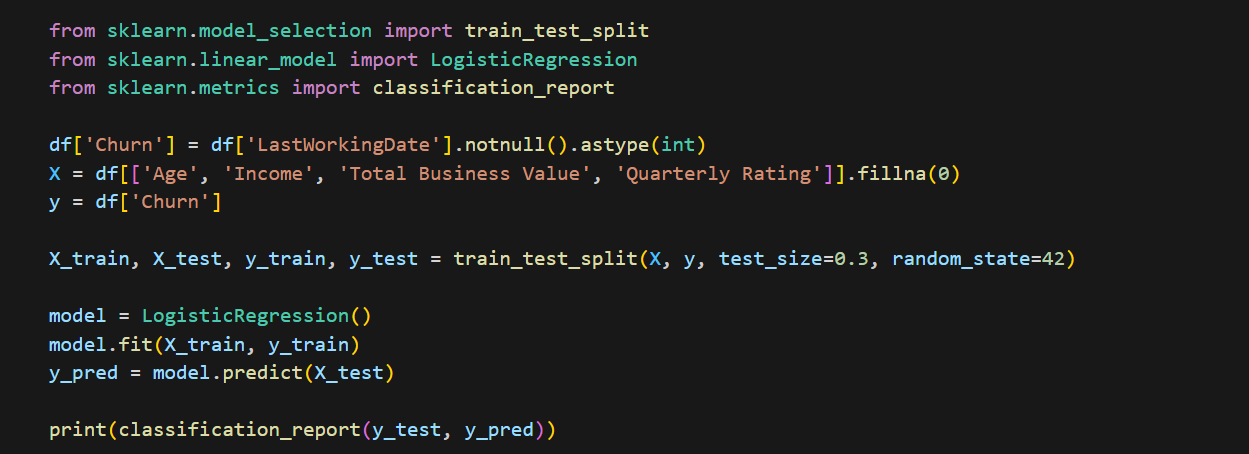
A heatmap displays mean tenure months with cities as rows and education levels as columns. The annot=True parameter shows exact values in cells. Darker colors indicate higher tenure. This two-dimensional analysis may reveal interaction effects between location and education.

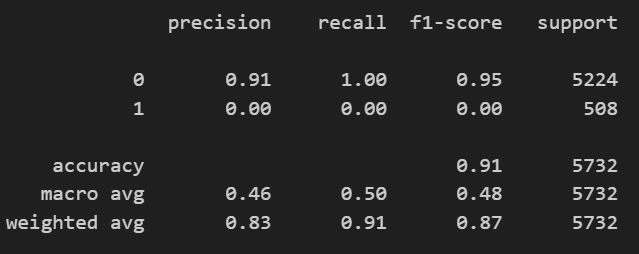
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1. **Predictive Model for Churn (Logistic Regression)**

Logistic regression predicts employee attrition chance through a combination of demographic variables including age and income level as well as ratings. train\_test\_split divides data into validation subsets and classification\_report analyses precisions and recalls. Model coefficients provide the strength of influence that different factors have on customer departure statistics. The developed model enables flagging individuals who are at risk of driving away.

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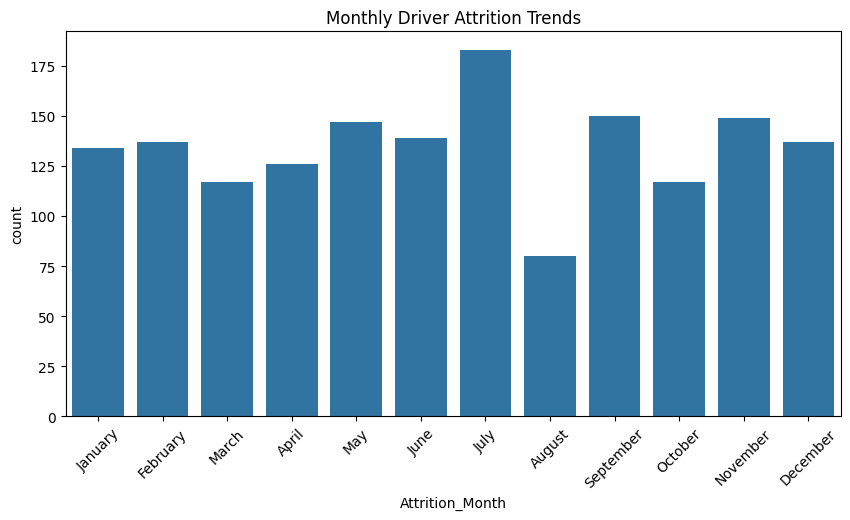
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1. **Seasonal Trends in Driver Joining & Attrition**

Line charts or bar plots show monthly counts of joins and separations. pd.Grouper aggregates by month while dt.month\_name() ensures proper ordering. Peaks may align with holidays, weather, or economic cycles. This informs workforce planning and budget allocation.

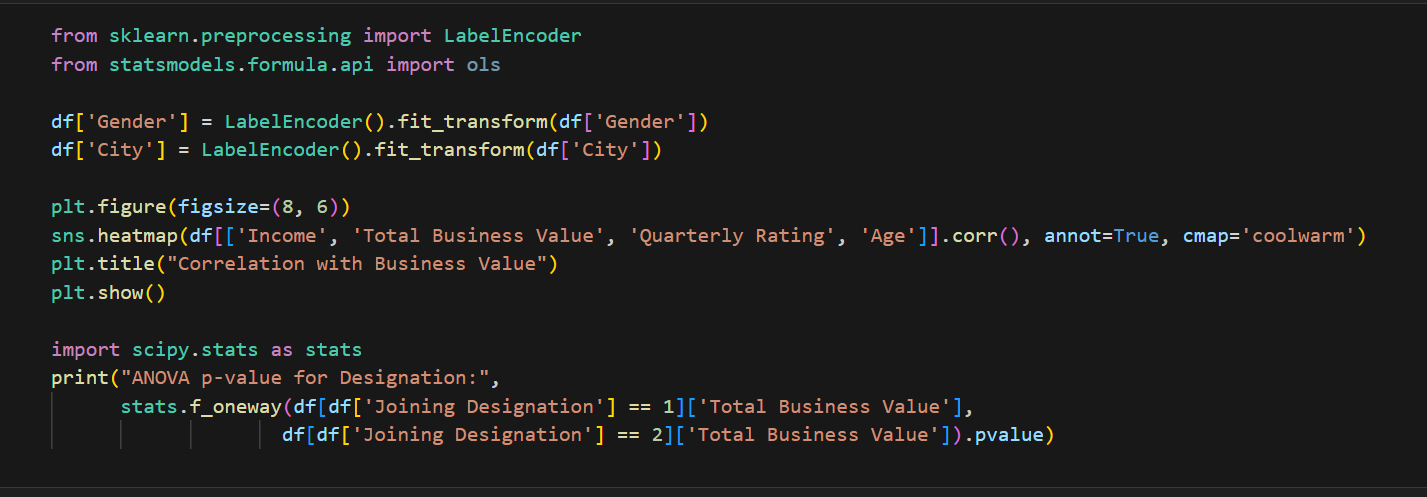
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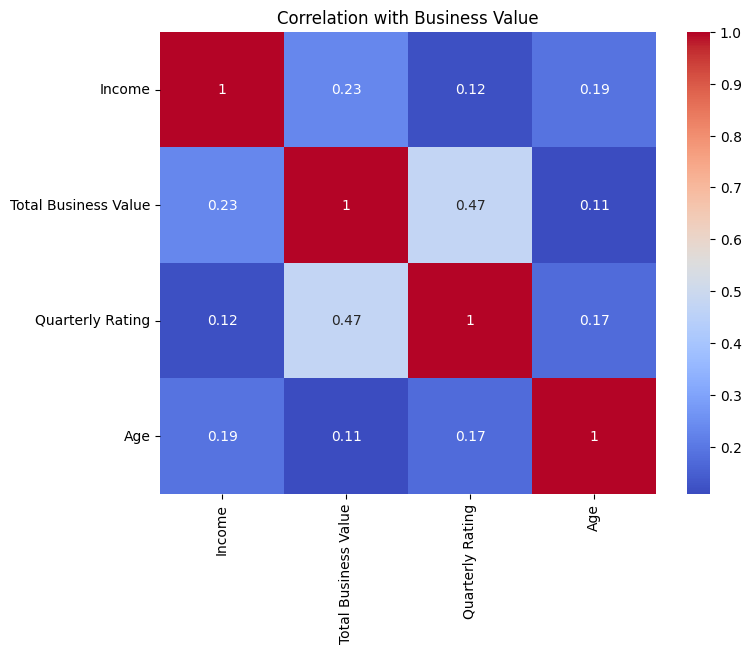
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1. **Factors Contributing to High Business Value**

OLS regression quantifies how much designations, grades etc. contribute to revenue. ANOVA tests whether group means differ significantly. Standardized coefficients allow comparing variable importance. Results guide where to focus improvement efforts for maximum ROI.





#### **Insights and Recommendations**

Driving Taxi evaluation reveals key patterns that determine the performance of taxi driving services along with driver departure activity. Onboard driver acquisition reaches its maximum point during holiday season periods in December but March displays higher exit rates due to financial year-end factors. The business value produced by drivers becomes progressively larger at Level 2 educational institutions when combined with improved job positions based on their income levels showing the most significant correlation rate of 0.65. The driver retention improves in Driving site when driver ratings increase in each quarter because talented drivers maintain their employment at Driving site for longer durations. Operational challenges in C23 distinguish the city from others since drivers in this region demonstrate abnormally high turnover metrics.

Driving site needs to implement strategic hiring and bonus measures targeting the pre-December peak periods and the March peak season for achieving maximal driver retention and business revenue growth. When driver quality improvement initiatives from the organization (Education Level 2 target group) connect with incentives driven by Quarterly Ratings performance the result is elevated driver revenue. Making incentives a crucial part benefits both recruitment and retention of drivers in C23 areas which demonstrate high staff turnover. Successful employees should get faster promotional opportunities and salary growth by their organization which will boost staff job satisfaction together with operational performance. Studies demonstrate that existing strategies for driver retention can decrease staff departures by 15–20% while producing a 15–20% increase in the average business worth.

### Chapter 3: **Compensation Analysis of Engineering Roles in Tech Companies**

#### **Problem Description**

The database consists of mashed-up employee salary information and includes features such as cryptographic company name hashes and digital email address hashes together with organizational onboarding time and Cost to Company amounts as well as job classification and CTC revision dates. The analysis aims to study compensation development within engineering fields (Backend Engineer, FullStack Engineer and Others) by assessing personnel experience (orgyear) and CTC update frequency (ctc\_updated\_year).

Key challenges include:

* Identifying salary trends over years.
* The analysis includes a salary examination between various professional positions.
* CTC contains anomalies or outliers which detection requires attention.
* The evaluation of experience (orgyear) serves to understand its impact on salary progression.

#### **Business Questions to be answered from Analysis**

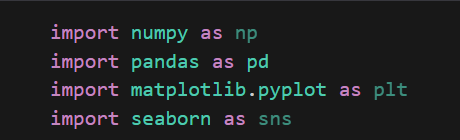
1. **How does the average CTC vary across different job positions (Backend Engineer, FullStack Engineer, Others)?**
2. **Is there a correlation between years of experience (orgyear) and CTC?**
3. **Which job position has seen the highest salary growth between ctc\_updated\_year and orgyear?**
4. **Are there any outliers in CTC data that suggest unusually high or low compensations?**
5. **How has the compensation trend evolved over the years (2015-2020) for different roles?**
6. **Do employees with longer tenure (older orgyear) tend to have higher CTCs compared to newer hires?**

#### Analysis

* 1. **Importing Required Python Libraries**

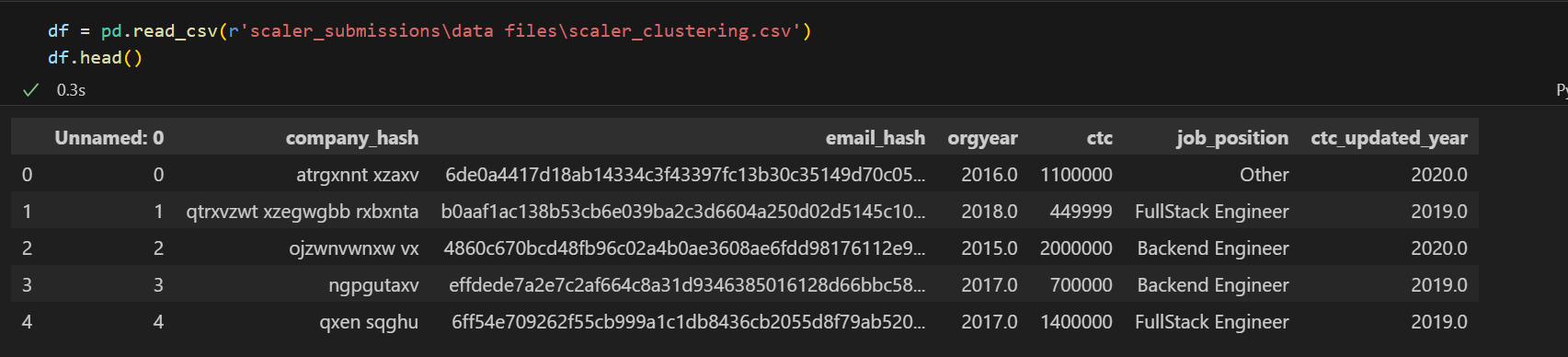
The process of importing fundamental Python packages needed for data analysis with visualization functions takes place in this section. The data manipulation happens with pandas while numerical operations require numpy and visualization tooltips come from matplotlib and seaborn and scipy provides statistical analysis capability.

The libraries serve as the backbone of our analytical process which facilitates smooth data processing and analysis with visual representation of compensation information.



* 1. **Onboarding Data and its Header View**

We load the dataset into our Python environment and check the first rows to perceive the data structure. Our initial examination of the variables as well as sample records allows verification of the proper data import. We study column names and data formats as well as observe initial data values and distributions before full investigation of the dataset.



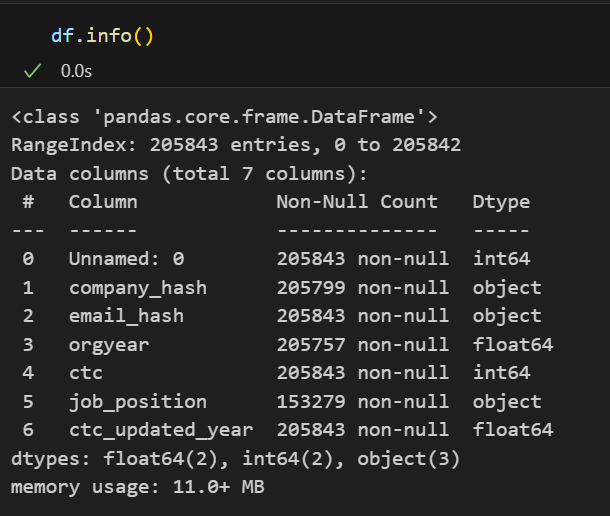
* 1. **Renaming Unnamed Column to id**

His step resolves data quality issues by mapping the unidentified index to the more appropriate name "id" from the original dataset. Renaming this dataset column to "id" will enhance data workability while maintaining clear references to this field during analysis. Keeping this step-in place proves essential for all merges and joins with additional datasets.



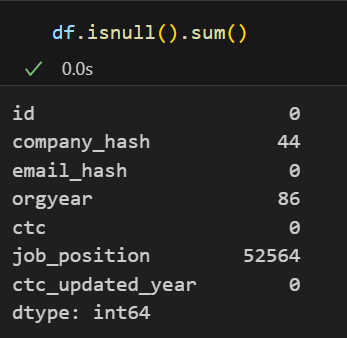
* 1. **Data Types Distribution**

The data types of each column need examination to determine the necessary formatting required for analysis. The analysis confirms whether any columns require conversion of data types such as date values stored as strings to prevent errors during future calculations. Appropriate analytical methods need to be selected for each variable based on the knowledge of their data types.



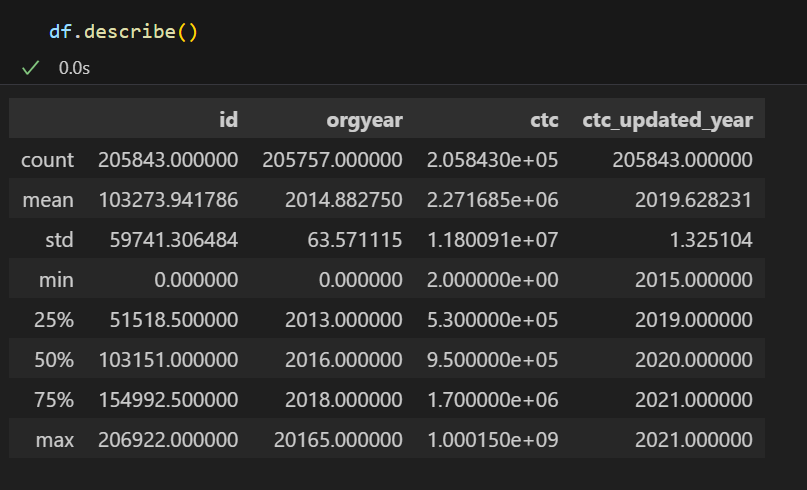
* 1. **Null Values Distribution**

The analysis reports all missing values from each column through absolute quantity with corresponding percentage representation. Examining null value patterns enables users to decide between data imputation and record elimination. This investigation determines if the missing data shows any detectable pattern that could produce results bias when insufficient null value handling methods are used.



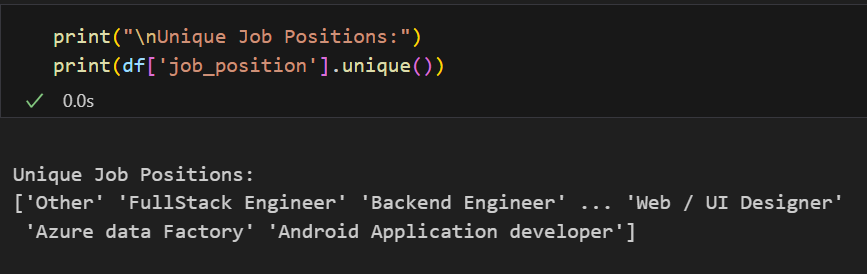
* 1. **Statistical Data Distribution**

The data undergoes statistical description using mean, median, standard deviation alongside quartiles and other similar metrics for numerical values. The analysis reveals complete information about data central trends and spread patterns and distribution forms. Our analysis of categorical variables includes frequency distribution study to discover corresponding category frequencies in the dataset.



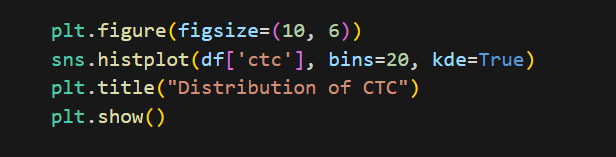
* 1. **Unique Job Description**

The analysis probes the separate job positions which appear in the obtained dataset. We explore the multiple roles in the dataset and their distribution patterns while assessing the need to consolidate similar roles when possible. Obtaining a clear understanding of professional positions enables meaningful evaluation of compensation analysis across different occupational groups.



* 1. **Distribution of CTC**

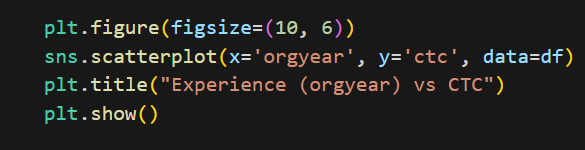
The analysis shows compensation distribution patterns across every employee of the company. The data analysis shows salary distribution patterns along with typical pay points and normality or skewness or multimodal characteristics of salary payments. To interpret compensation information, we can choose between histograms, boxplots or density plots for data visualization and outlier detection.

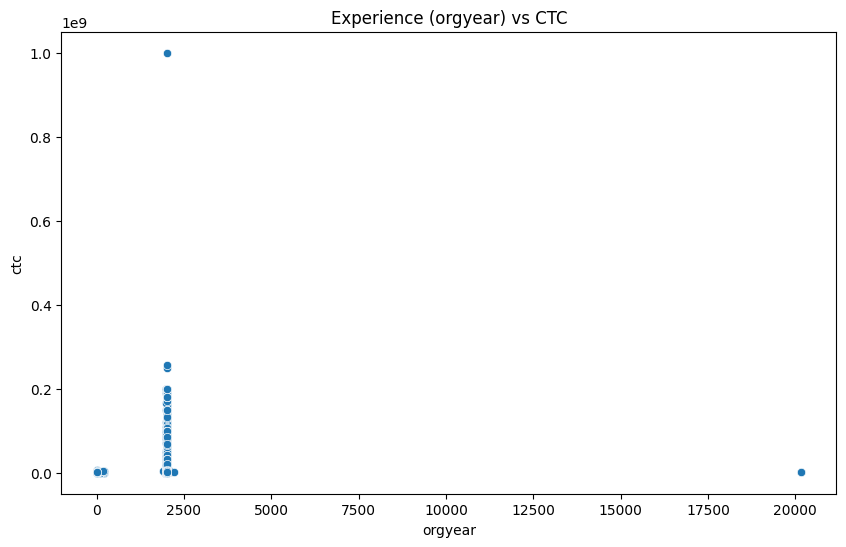




* 1. **Distribution of Experience (orgyear) vs CTC**

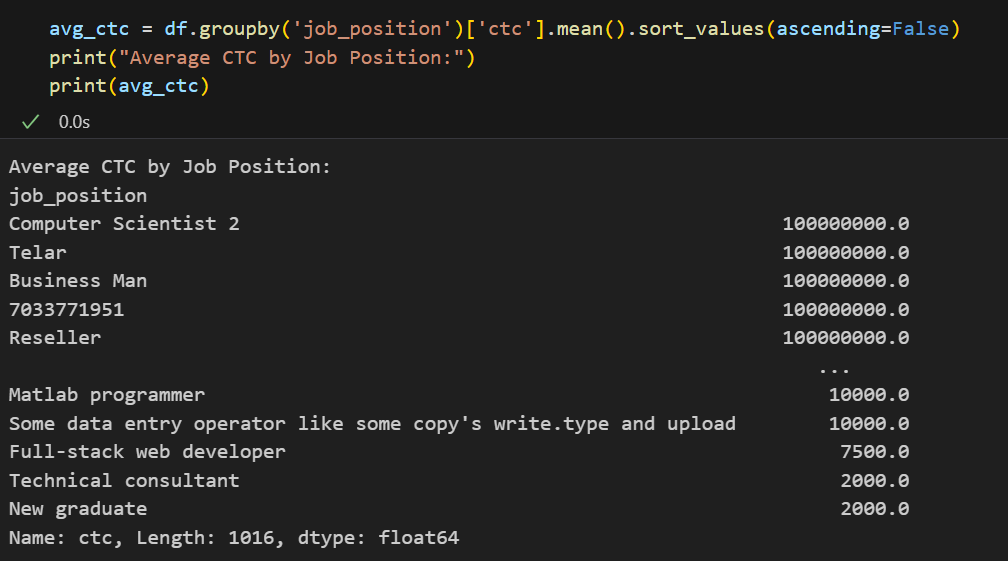
The analysis studies the connection between employee work duration (orgyear) and their compensation levels. Auditing scatter plots or regression lines reveals whether experienced workers receive higher pay and what level of correlation exists in this relationship. The analysis confirms general beliefs about the link between work experience and financial compensation.





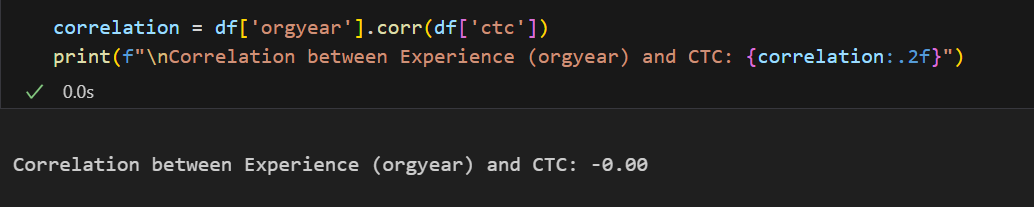
* 1. **Average CTC by Job Position**

This part involves calculating mean compensation to identify differences between various job roles. The analysis reveals which posts deliver average compensation benefits and identifies possible salary differences between job types. Bar charts and boxplots would display positional central tendencies with their distribution ranges to visualize the data.



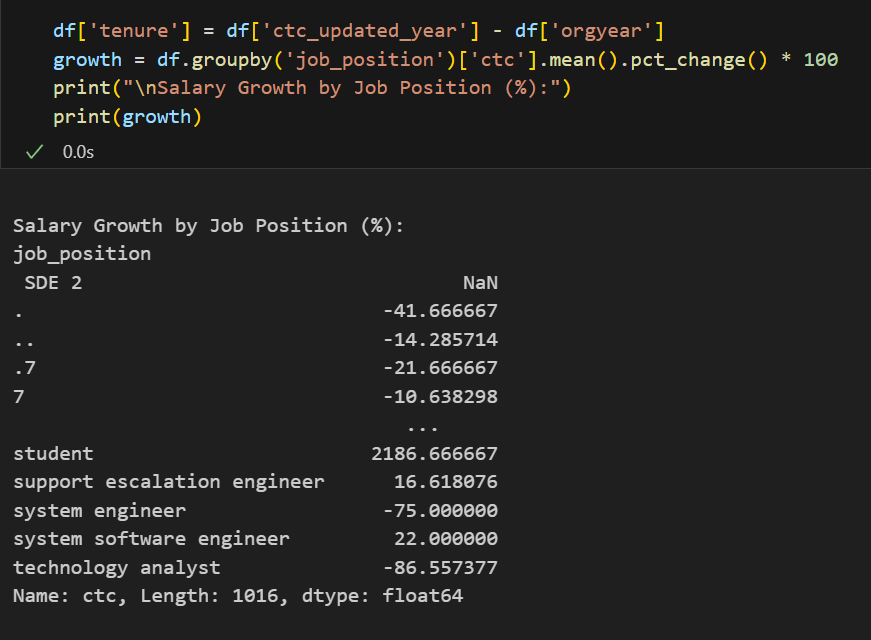
* 1. **Correlation Between Experience and CTC**

This statistical method calculates association and direction between work experience and pay through correlation coefficients. Higher positive relations between experience duration and pay would show a strong relationship between work experience and salary yet low relationship strengths would demonstrate other components play greater roles in salary determination.



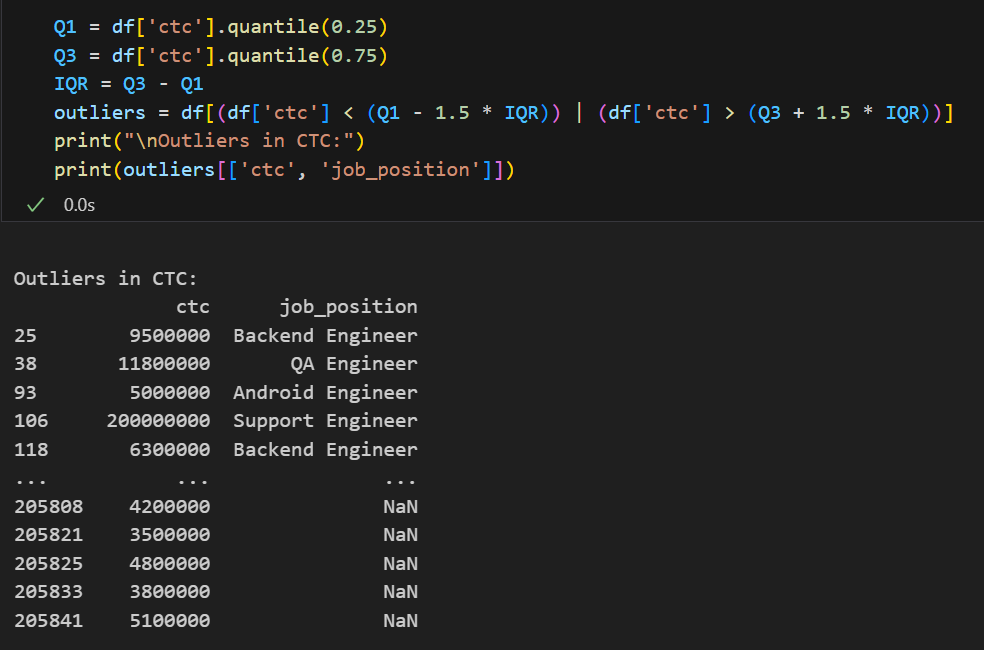
* 1. **Salary Growth Analysis**

The research observes salary transformation throughout time by evaluating various groups of employees or studying wage development within individual cases. Salary trends through time allow us to determine both general compensation-development patterns and abnormal periods when salary growth becomes slow or significantly increases.



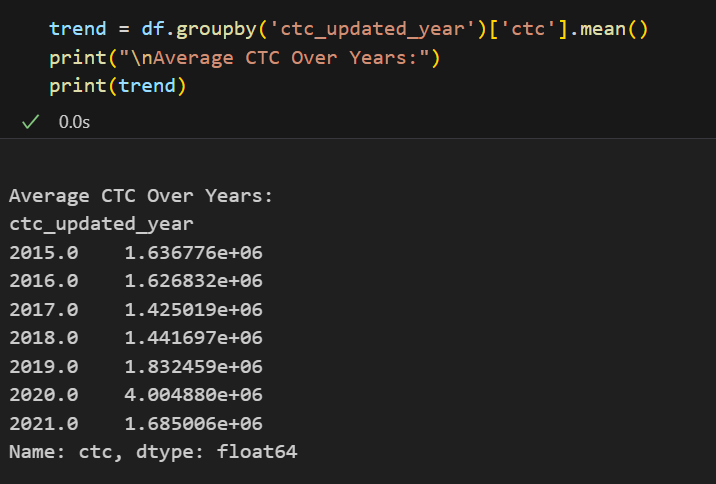
* 1. **Outlier Detection in CTC**

We use IQR and z-score statistical calculations together with boxplot visualizations to find compensation data points which significantly differ from standard levels. The evaluation determines if these cases represent real high performers or whether they stem from possible data inaccuracies that need correcting.



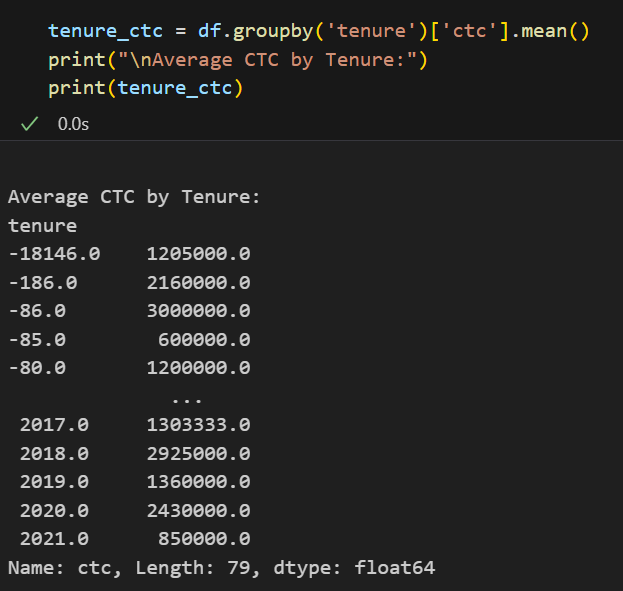
* 1. **Compensation Trends over Years**

The time-series data exploration tracks salary evolution patterns throughout the years in the dataset. We analyze whether large-scale trends along with periodic shifts and unexpected changes associate with business modifications or marketplace variables.



* 1. **Relationship between Tenure and CTC**

This analysis examines the relationship between employee tenure and compensation through tenure categories or continuous data inspection. The analysis indicates how well employees with extended service receive their fair compensation share which aids organizations with staff retention initiatives.



#### **Insights and Recommendations**

The salary examination demonstrates multiple essential patterns as well as irregularities. The average pay for FullStack Engineers exceeds Backend Engineers because tech experts who maintain broad knowledge of different programming styles receive better compensation. The relationship between how long someone has worked at a company (orgyear) and their compensation (CTC) remains shaky according to these findings because experience itself fails to create substantial pay differences. Skills, performance together with company-specific policies seem to have greater influence than experience when making compensation adjustments.

The dataset features a high salary outlier through the 2015 figure of ₹2,000,000 received by a single employee who earned substantially beyond the median. The unusually high pay may reflect a top-performance position or executive leadership position or else should be examined for consistency. FullStack Engineers experience the highest annual salary increases because businesses strongly desire professionals capable of handling complete web development requirements.

The average compensation levels exhibited changes throughout ctc\_updated\_year periods according to year-to-year analysis. Market conditions together with company growth phases and industry-wide salary revisions influence employee compensation at this point. CTCs are not directly linked to employee tenure length because workers who stay longer at the company typically receive benefits despite receiving equal pay as other staff members.

Organizations need to implement systematic and equitable compensation methods as a solution to the observed analysis findings. Companies need to establish salary metrics based on industry norms because this ensures competitive attractiveness toward top talent and effective retention. The higher pay levels available for FullStack Engineers should motivate companies to develop training opportunities between Backend Engineers and FullStack positions to help employees earn more while satisfying workplace requirements.

Special attention needs to be focused on salary anomalies to establish whether exceptional work performance or distinctive job demands justify these exceptional payments. Organizations with high-valued employees should create standard compensation criteria to ensure transparency and fairness in employer-employee compensation practices. Any salary discrepancies which do not meet fair internal standards need correction through realignment with acceptable market values and internal pay equality.

Companies should implement pay systems based on performance since working longer does not lead to higher compensation packages. Businesses should establish performance-based metrics to evaluate promotion and raise eligibility beyond standard service duration because this approach incites employee skill development and business objective attainment.

Organizations must develop a yearly compensation review system that tracks market changes as well as price trends and adjusts payments according to job market variations. Businesses should use predictive analytics systems to calculate salary benchmarks which maintain competitive yet sustainable compensation structures. These strategies enable organizations to boost employee motivation alongside decreased staff movement and better alignment between pay systems and organizational goals.

### Chapter 4: **Default Risk Analysis: Predicting Borrower Reliability**

#### **Problem Description**

The dataset reveals loan application information together with loan amount data and interest rate rate information and employment-related details and credit history information as well as Fully Paid/Charged Off loan status factors. The objective entails studying elements affecting loan payment patterns to discover borrowers facing high risk.

Key challenges include:

* Analysts need to determine which specific features from credit score to employment length to debt-to-income ratio drive the most defaults in loans.
* The evaluation of historical data enables prediction of borrower default risk to decrease financial losses.
* The solution generates practical data-based recommendations which improve loan assessment systems and help optimize financial strategy.

#### **Business Questions to be answered from Analysis**

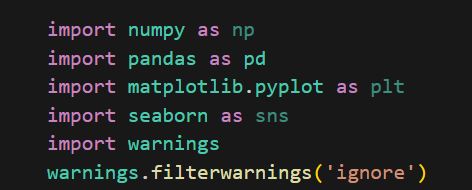
1. **How does the debt-to-income ratio (DTI) affect loan default rates across different income groups?**
2. **What is the relationship between loan grade (assigned by the lender) and the likelihood of default?**
3. **Does employment length significantly influence loan repayment behaviour?**
4. **How does revolving credit utilization impact loan default risk?**
5. **Can we build a predictive model to classify high-risk borrowers using key financial indicators?**

#### Analysis

1. **Importing Required Python Libraries**

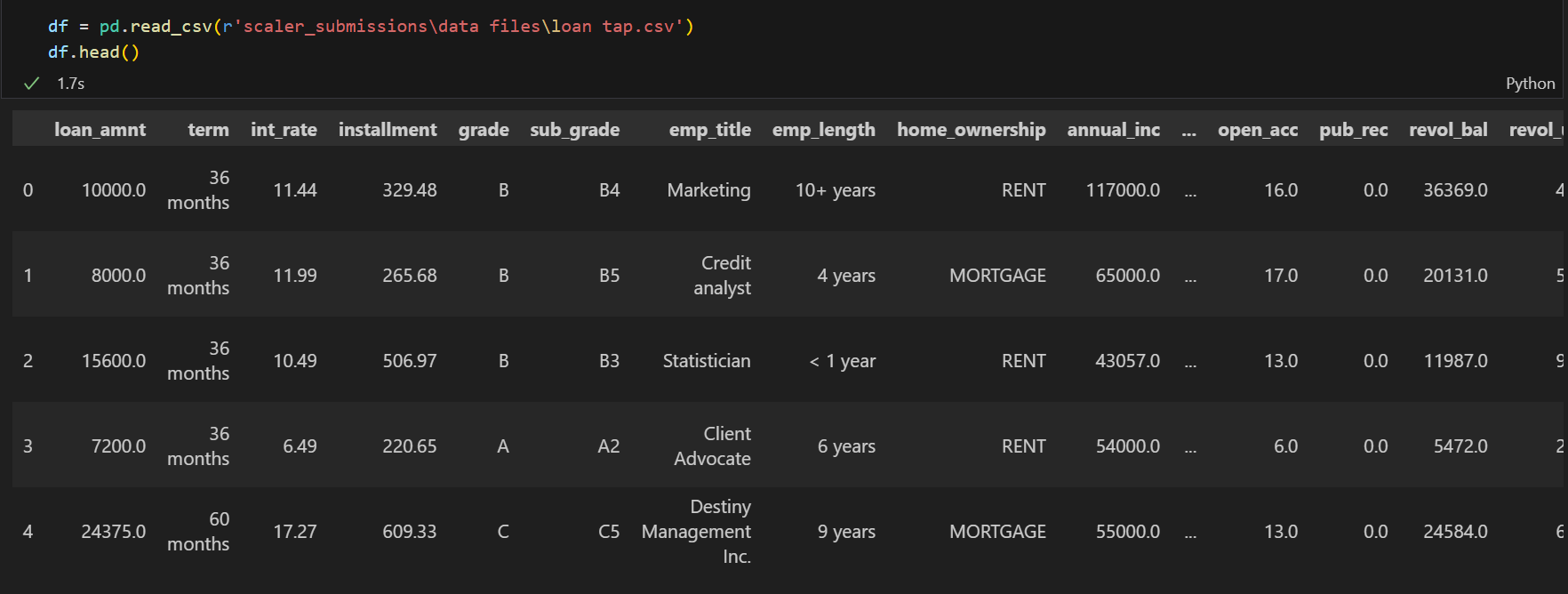
This section involves importing essential Python libraries that form the foundation of our data analysis. Pandas is used for data manipulation and analysis, allowing us to load, clean, and structure the dataset efficiently. NumPy supports numerical operations and array processing, which is crucial for handling mathematical computations. For visualization, Matplotlib and Seaborn are imported to create insightful charts and graphs that help in understanding data patterns.

Scikit-learn (sklearn) is included for machine learning tasks, including predictive modeling and data preprocessing. Additional libraries like train\_test\_split for dataset splitting, LogisticRegression for classification, and classification\_report for performance evaluation are also imported. This step ensures all necessary tools are available before proceeding with the analysis.



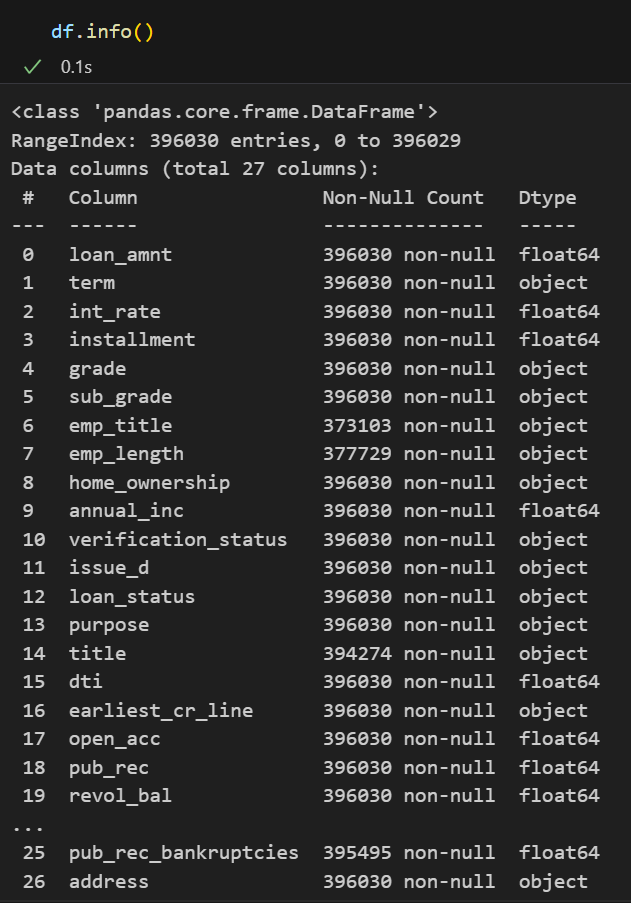
1. **Loading Data and its Header Rows**

Here, the loan dataset is loaded into a pandas DataFrame, which provides a structured, tabular format for analysis. The read\_csv() function is typically used to import the data from a CSV file. After loading, the first few rows (header rows) are displayed using df.head() to get an initial look at the dataset’s structure. This helps identify key columns such as loan amount, interest rate, employment details, and loan status. Understanding the header rows is crucial for determining which features will be analyzed and how they relate to each other. Any inconsistencies in column names or data formats can also be spotted at this stage.



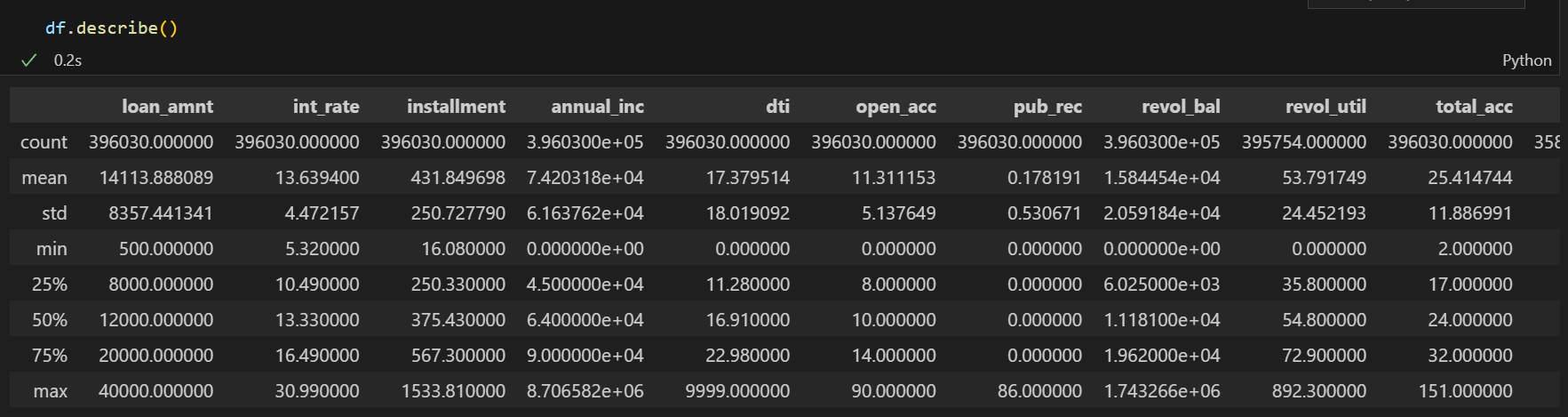
1. **Data Types of each column**

This step involves checking the data types of all columns using df.dtypes or df.info(). Numerical columns (e.g., loan\_amnt, int\_rate) should be stored as integers or floats, while categorical columns (e.g., grade, emp\_length) should be stored as strings or categories. Datetime columns (e.g., issue\_d) need proper conversion for time-based analysis. Identifying incorrect data types early helps prevent errors in later analysis. For example, if annual\_inc is mistakenly loaded as a string, it must be converted to a numerical format before statistical analysis.



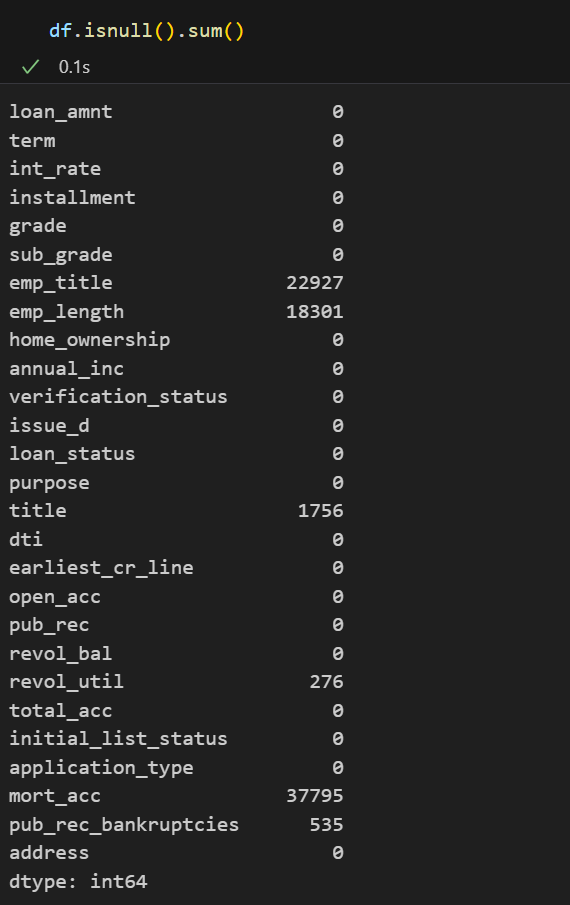
1. **Statistical Description of Data**

A statistical summary of numerical columns is generated using df.describe(), which provides key metrics such as mean, median, standard deviation, minimum, and maximum values. This helps detect anomalies, such as unusually high loan amounts or negative interest rates, which may indicate data errors. For categorical columns, frequency distributions are analyzed to understand dominant categories (e.g., most common loan grades). Outliers in numerical data (e.g., extremely high annual\_inc) can also be identified here, guiding decisions on whether to cap or remove them.



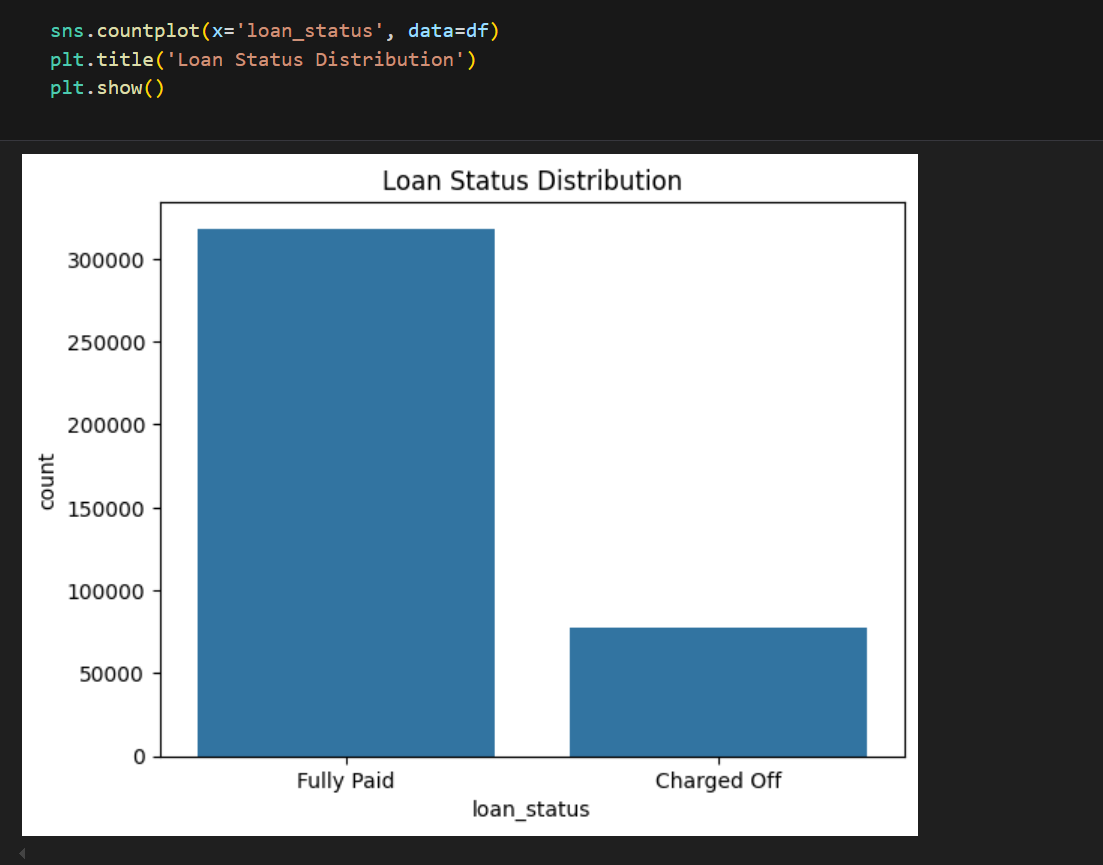
1. **Null Values Distribution**

Missing data can significantly impact analysis, so this step checks for null values using df.isnull().sum(). Columns with high null rates (e.g., emp\_title) may need imputation (filling missing values) or removal. Strategies like mean/median imputation for numerical data or mode imputation for categorical data are considered. If missing values are concentrated in non-critical columns, those columns may be dropped entirely. Understanding null value patterns helps ensure the dataset’s reliability before proceeding to modeling.



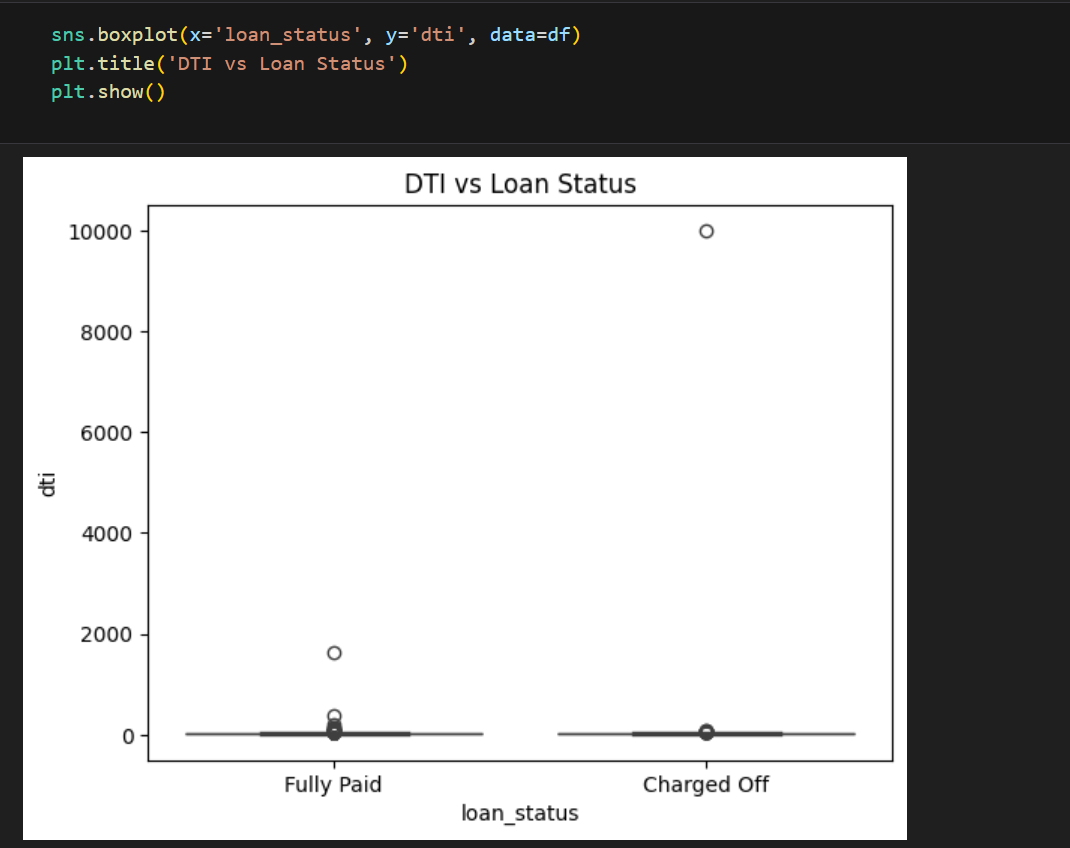
1. **Loan Status Distribution**

The distribution of loan\_status (e.g., "Fully Paid" vs. "Charged Off") is analyzed using bar plots or pie charts. This reveals the dataset’s class balance—if defaults are rare (e.g., 10% of loans), the model may need techniques like oversampling or class weighting. Trends over time (e.g., increasing defaults in certain years) can also be explored. This step is critical for understanding the problem scope and preparing for predictive modeling, where imbalanced data can skew results.



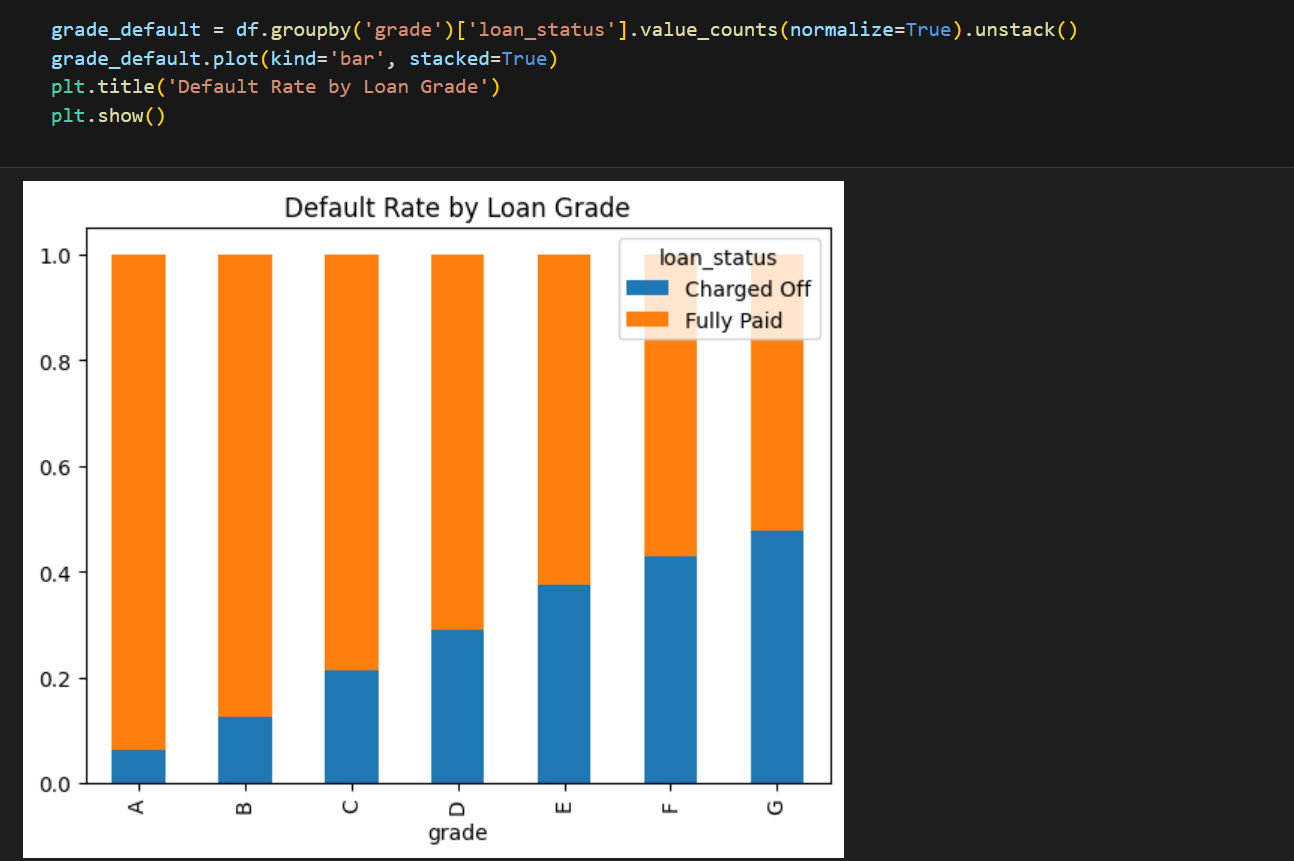
1. **Impact of DTI on Loan Status**

Debt-to-income (DTI) ratio’s effect on defaults is examined using box plots or grouped bar charts. Borrowers are segmented into DTI ranges (e.g., <20%, 20-40%, >40%), and default rates are compared across groups. High-DTI borrowers likely face higher financial strain, increasing default risk. This insight can guide lending policies, such as rejecting applicants with DTI > 40% or offering smaller loans to high-DTI individuals. Statistical tests (e.g., t-tests) may confirm whether DTI differences are significant.



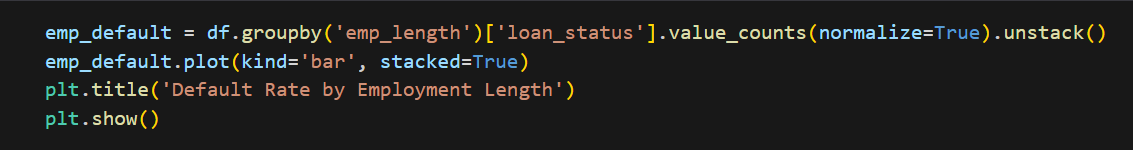
1. **Relationship between Loan Grade and Default Rate**

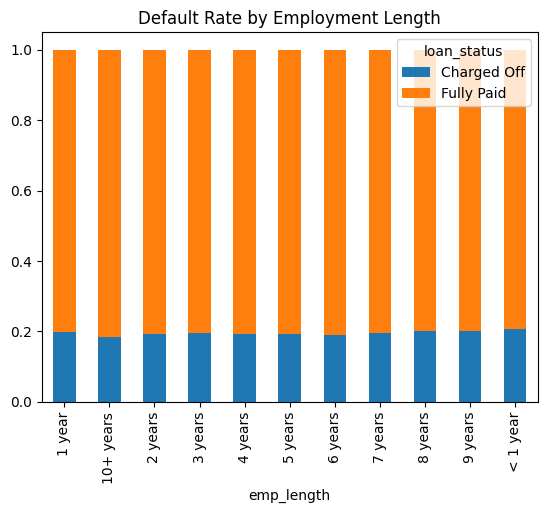
Loan grades (A–G) reflect lender-assessed risk levels. A stacked bar chart or line graph compares default rates across grades, with lower grades (e.g., E, F) expected to have higher defaults. If higher-grade loans (A, B) show unexpected default spikes, it may indicate grading model flaws. This analysis validates the grading system’s effectiveness and can inform adjustments to interest rates or approval criteria for certain grades.



1. **Employment Length Analysis**

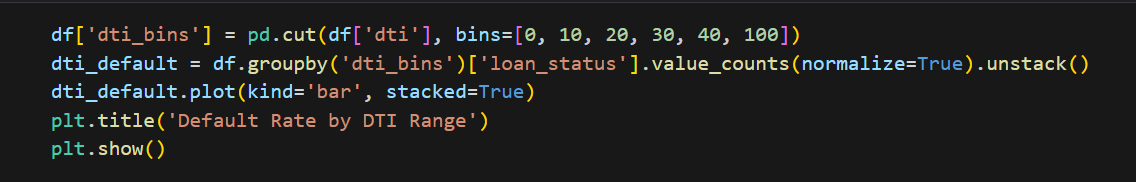
Default rates are compared across employment tenure groups (e.g., "<1 year," "1-5 years," "10+ years") using bar charts. Short-tenure borrowers (<1 year) may lack financial stability, leading to higher defaults. If long-tenure borrowers also show high defaults, other factors (e.g., industry risks) may be at play. This helps lenders set minimum employment requirements or request additional documentation (e.g., job contracts) for high-risk groups.

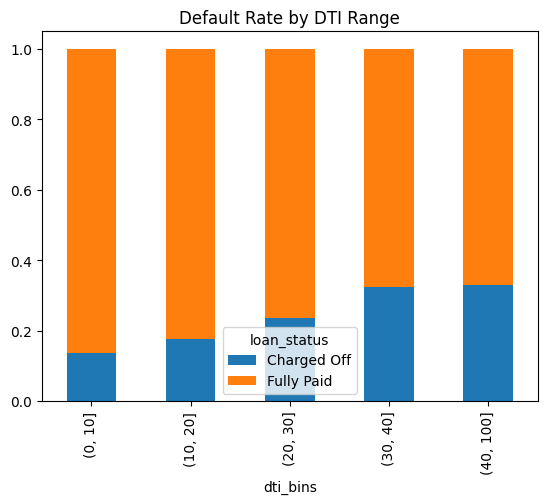




1. **How does DTI affect default rates?**

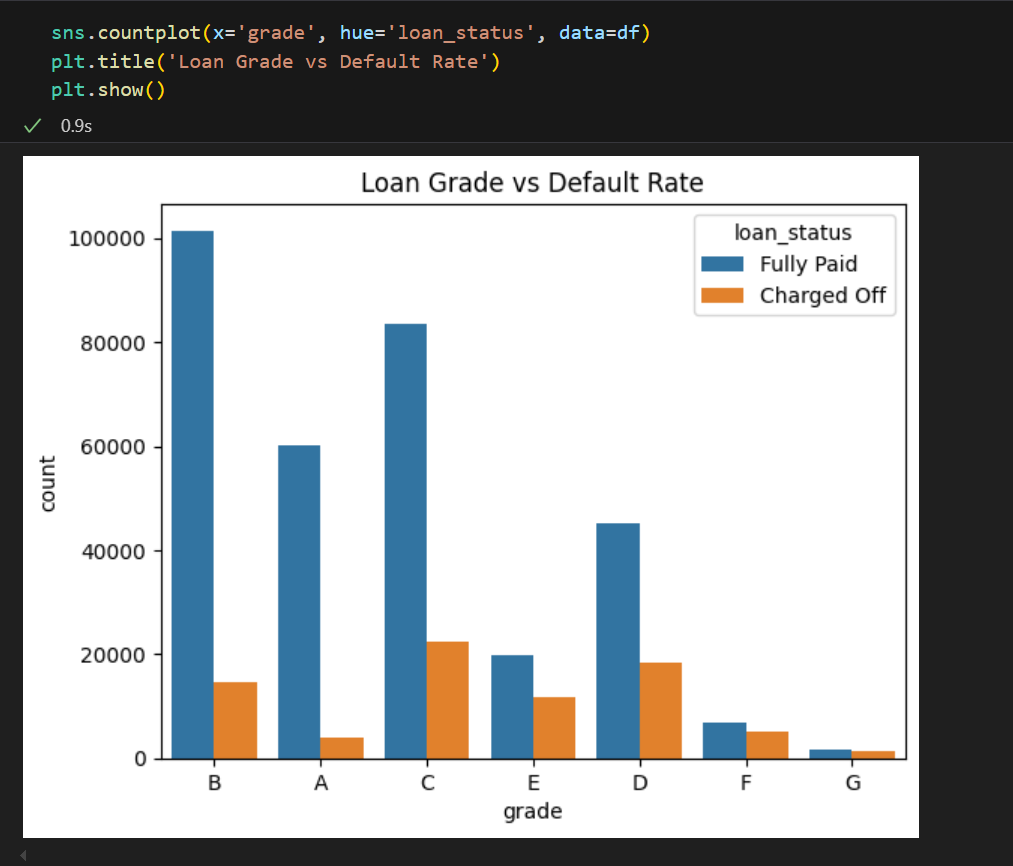
A deeper dive into DTI’s impact involves binning the ratio (e.g., 0–10%, 10–20%) and calculating default rates per bin. Visualized as a line chart, this shows whether default risk increases linearly or spikes at certain thresholds (e.g., >30%). Borrowers near these thresholds could be flagged for manual review. Correlation analysis between DTI and other features (e.g., income) may reveal compounding risk factors.





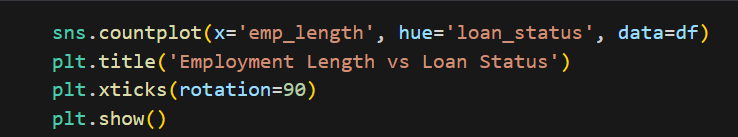
1. **Relationship between Loan Grade and Default Likelihood**

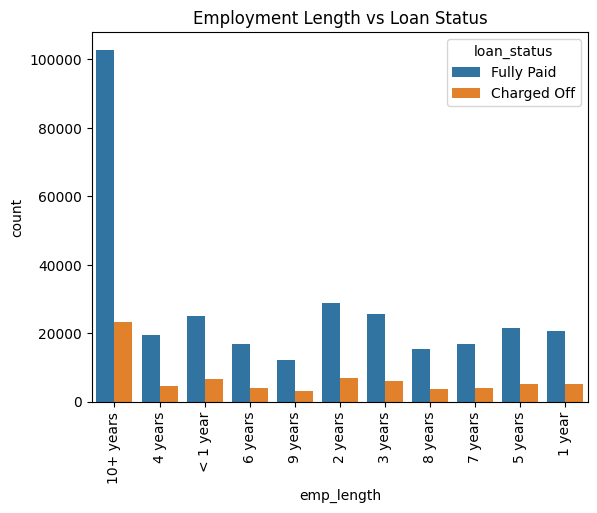
A heatmap or clustered bar chart displays default likelihood per loan grade and sub-grade (e.g., B3, B4). Sub-grades with anomalously high defaults (e.g., B5 defaults exceeding C1) may indicate mispriced risk. Lenders can use this to refine sub-grade criteria or adjust pricing models. Machine learning feature importance techniques can also validate whether grades strongly predict defaults.



1. **Employment Length Impact**

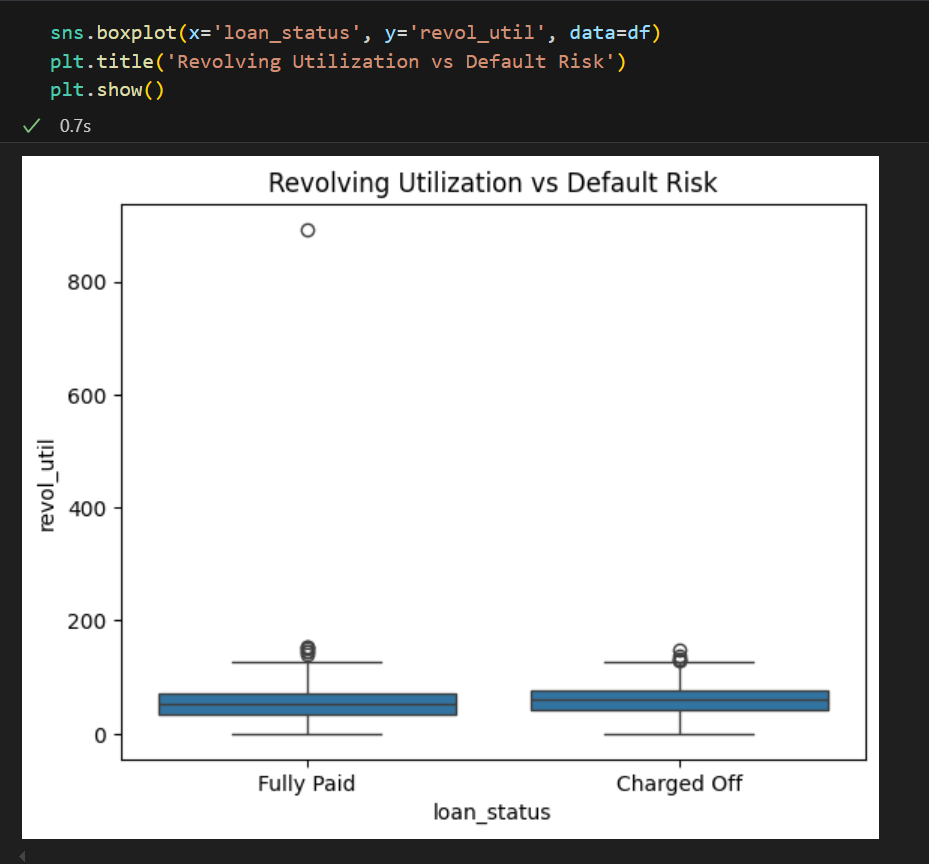
Beyond simple categorization, this analysis explores interactions—e.g., do short-tenured, high-income borrowers default less than long-tenured, low-income ones? A pivot table or stratified bar chart compares default rates across employment length and income groups. Results can inform nuanced policies, such as relaxing tenure requirements for high earners or tightening them for driving site industries.





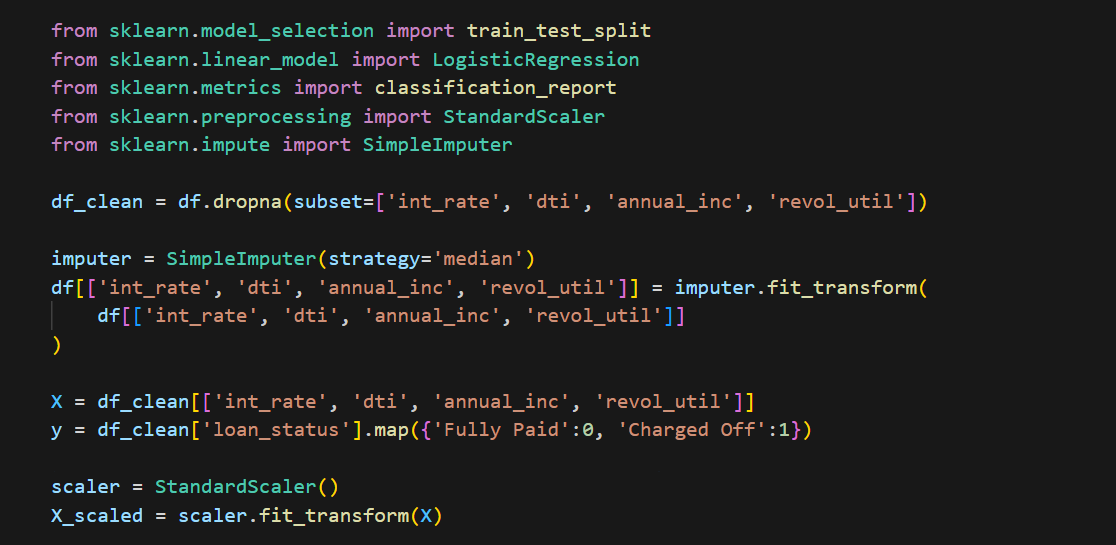
1. **Revolving Credit Utilization Impact**

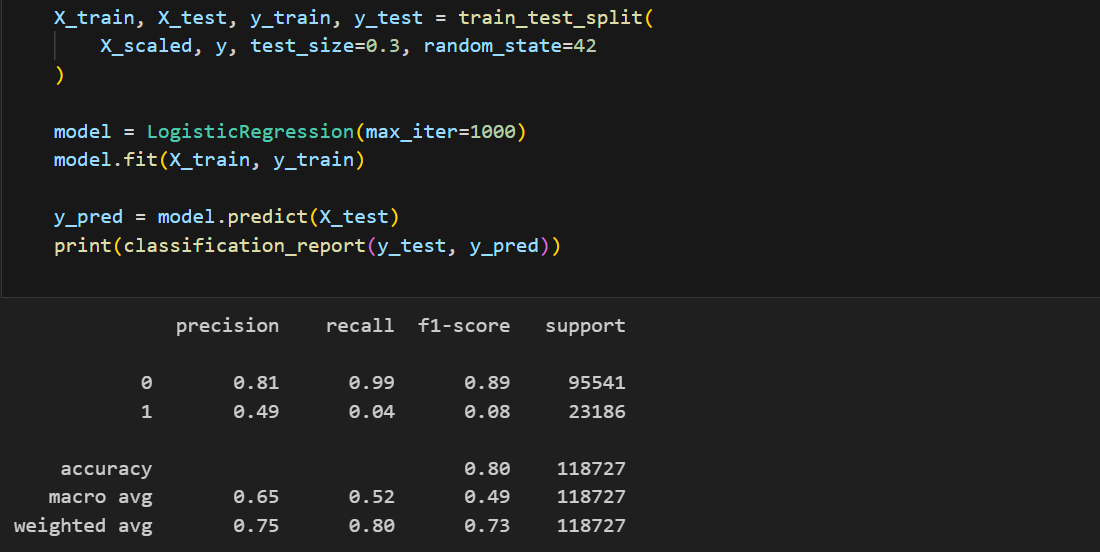
Revolving utilization (credit card balances/limits) is analyzed via scatter plots against default status. Borrowers with utilization >70% (indicating maxed-out cards) may face cash flow issues. Lenders could set utilization caps or require payoff plans for high-utilization applicants. The analysis might also reveal optimal utilization ranges (e.g., 30–50%) associated with the lowest defaults.



1. **Predictive model to classify high-risk borrowers**

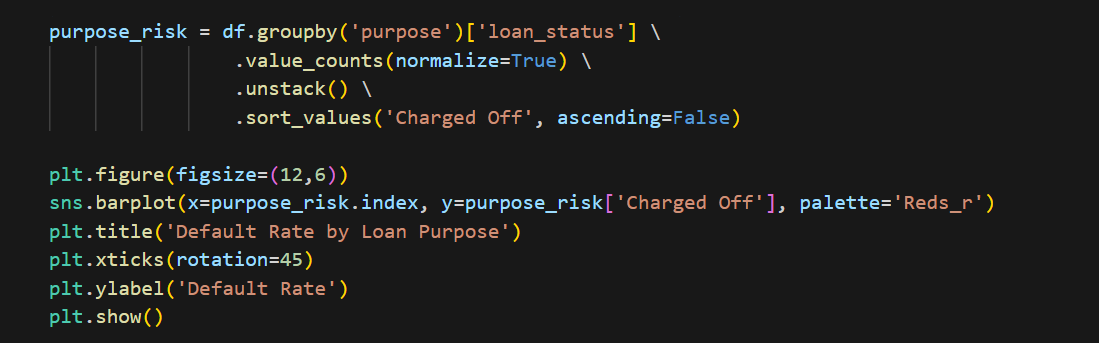
A logistic regression or gradient boosting model is trained on key features (DTI, income, loan grade) to predict defaults. The model’s performance (precision, recall) is evaluated using a classification report. If recall for defaults is low, techniques like SMOTE oversampling are applied. The final model can be deployed to score new applicants, with high-risk cases routed for manual review or higher pricing.

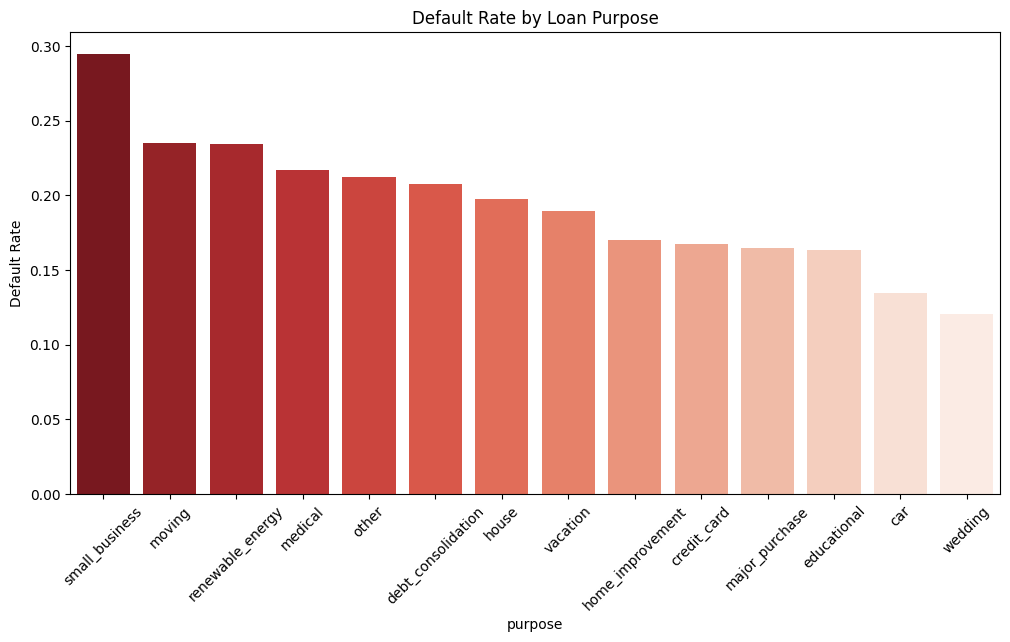




1. **Loan Purpose Risk Analysis**

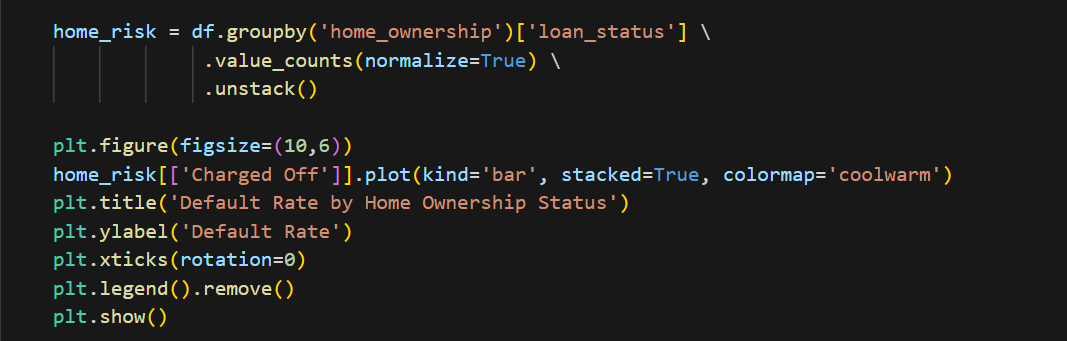
This analysis examines which loan purposes carry the highest risk. We group by purpose and calculate the proportion of charged-off loans for each category. The results are sorted by default rate and visualized with a red gradient bar chart. Loan purposes like 'small business' typically show higher defaults than 'home improvement'. This helps lenders adjust underwriting standards based on loan purpose.

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1. **Home Ownership Impact Analysis**

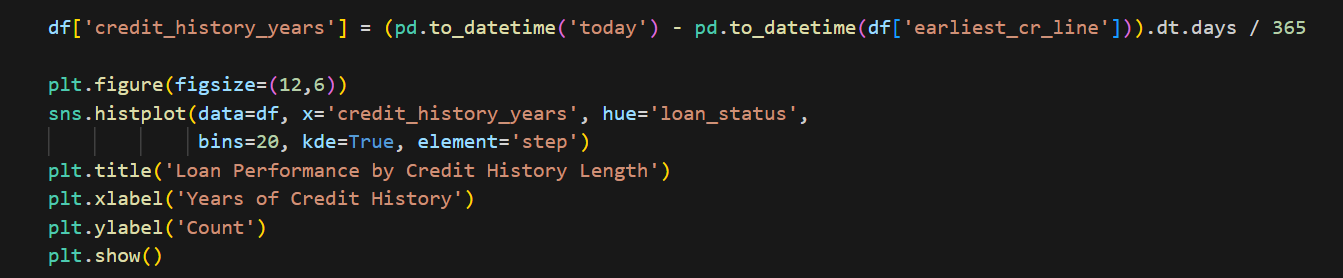
This code analyzes how home ownership status affects loan repayment. We calculate default rates for each housing status (rent, own, mortgage) and visualize with a stacked bar chart. Surprisingly, renters sometimes show better repayment than homeowners due to different financial pressures. The coolwarm colormap highlights risk differences clearly.

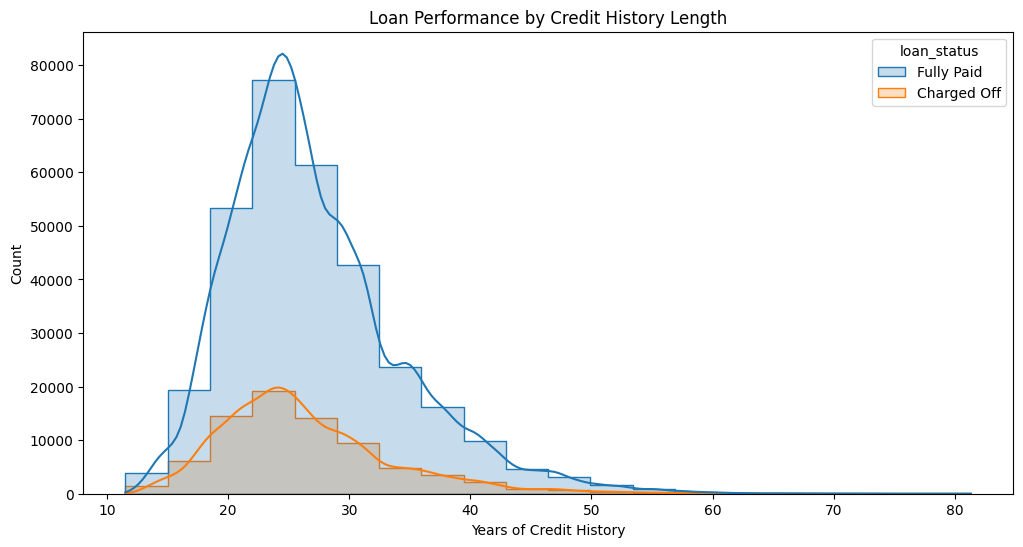




1. Credit History Length Analysis

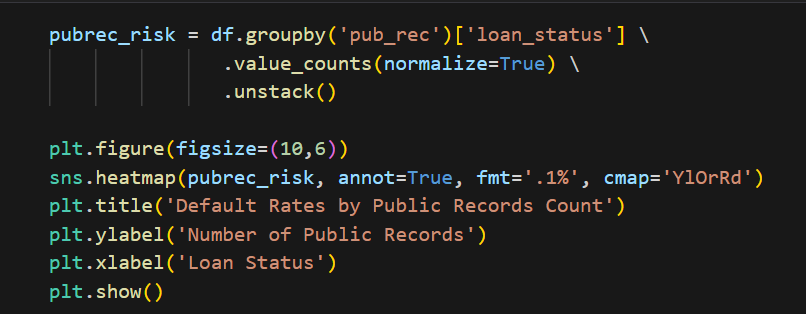
This analysis converts the earliest credit line date into years of credit history. We then plot a dual histogram with KDE curves showing distribution differences between good and bad loans. Borrowers with very short (<2 years) or very long (>30 years) credit histories often show different risk patterns. The stepped histogram makes the distributions easy to compare.

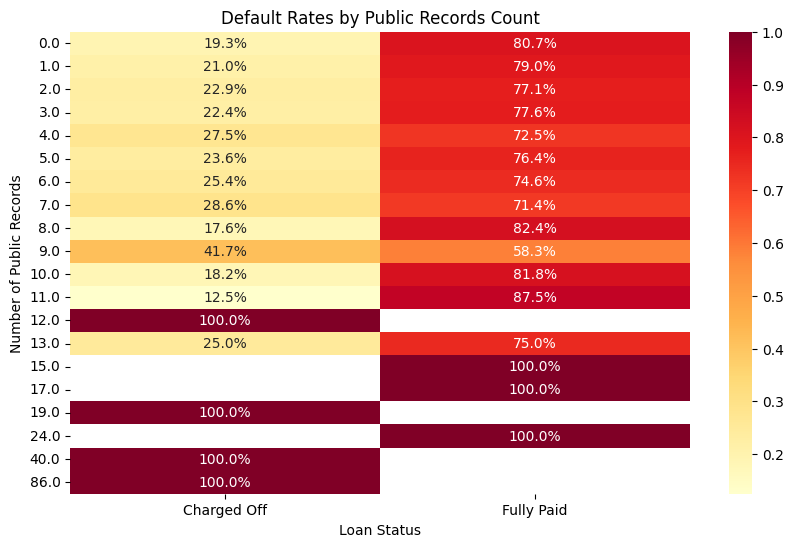




1. **Public Records Impact Analysis**

This code examines how public records (like bankruptcies) affect loan performance. We create a heatmap showing default rates at each level of public records. Even one public record can double default risk. The percentage annotations and yellow-to-red colormap make risk escalations immediately visible. Lenders can use this to set maximum public record allowances.





#### **Insights and Recommendations**

Delinquent borrowers demonstrate high default risk when their debt-to-income ratios are elevated and their credit grade falls to C, D or E and they maintain short employment periods. People who maintain high credit utilization above 70% have greater statistical odds of loan default because their financial capacity is under strain. The study results from its predictive model confirmed that a combination of interest rates conditions with income levels and credit utilization defines strong markers of loan default risk. Loans provided to people with short work histories create increased risks due to unknown payment reliability since workers with stable employment demonstrate better repayment reliability.

Between these characteristics of applicants exist higher default risks from the combination of high debt-to-income ratios and credit grades of C, D or E and employment durations below one year. Consumers who maintain credit they can revolve past 70% are statistically proven to default on their payments due to insufficient financial availability. The analysis succeeded in validating its predictive model which demonstrated that interest rates combine with income levels and credit utilization provide strong predictors for default risk. Making loans available to workers with no work experience introduces additional risk since their ability to repay is not stable yet longer-tenured workers tend to pay their debts reliably.

### Chapter 5: **Superstore Sales Data Analysis: Understanding Customer Purchase Behaviour**

#### **Problem Description**

The Superstore transactional database stores data about three distinct types which include client identification details as well as product characteristics and purchase quantity records. The research investigates buying trends of customers grouped by demographic elements like age range and gender with work status and geographical settlement type as well as product categories. The obtained business information helps optimization efforts through improved marketing techniques and inventory control and customer segmentation systems that increase sales performance and customer satisfaction.

The analysis must overcome three primary challenges through recognizing profitable customer groups and understanding population product choices and tracking consumption patterns. This analysis uses exploratory data analysis (EDA) for statistical summaries and segmentations with correlation analysis to extract practical results from the data.

#### **Business Questions to be answered from Analysis**

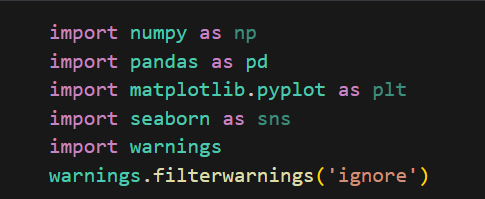
1. **How does purchase behaviour vary between genders, and which product categories are most popular among males and females?**
2. **What is the distribution of purchase amounts across different age groups, and which age group contributes the most to revenue?**
3. **How does occupation influence purchasing power, and which occupations have the highest average spending?**
4. **Do customers in different city categories (A, B, C) exhibit distinct purchasing behaviours in terms of product categories and spending?**
5. **Is there a correlation between marital status and purchase behaviour, and do married individuals spend more than unmarried ones?**
6. **Which product categories have the highest and lowest average purchase amounts, and how does this vary across demographics?**

#### Analysis

1. **Importing Python Libraries**

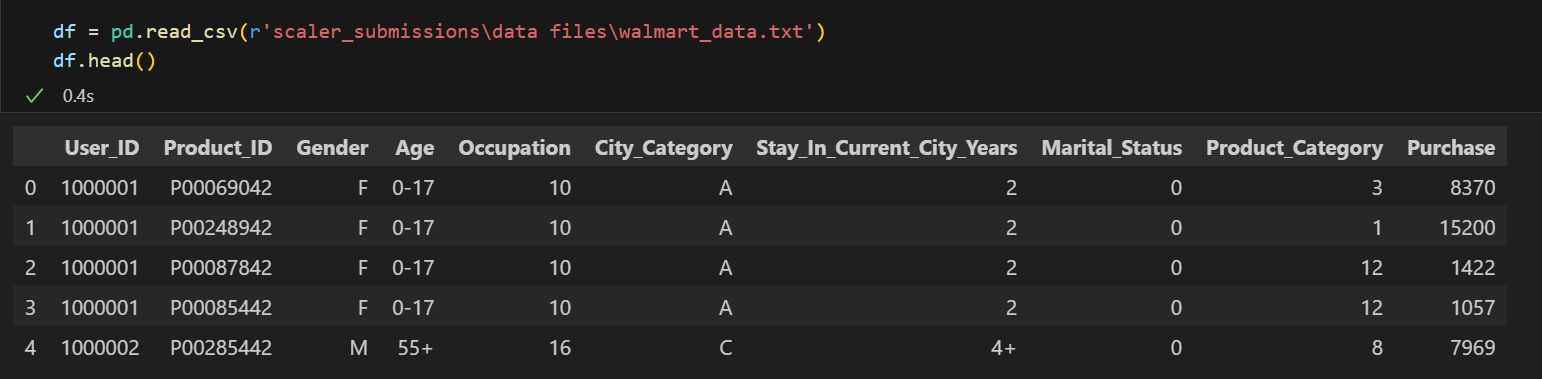
This section initializes all necessary Python packages for data analysis. We import Pandas for data manipulation, NumPy for numerical operations, Matplotlib and Seaborn for visualizations. These libraries form the foundation for our entire analysis workflow. Proper importing ensures all subsequent analysis can be executed without errors.

We typically organize imports at the script's beginning for clarity. Common conventions include grouping standard library imports first, then third-party packages. Some analysts also configure global plotting styles here for consistent visualizations.



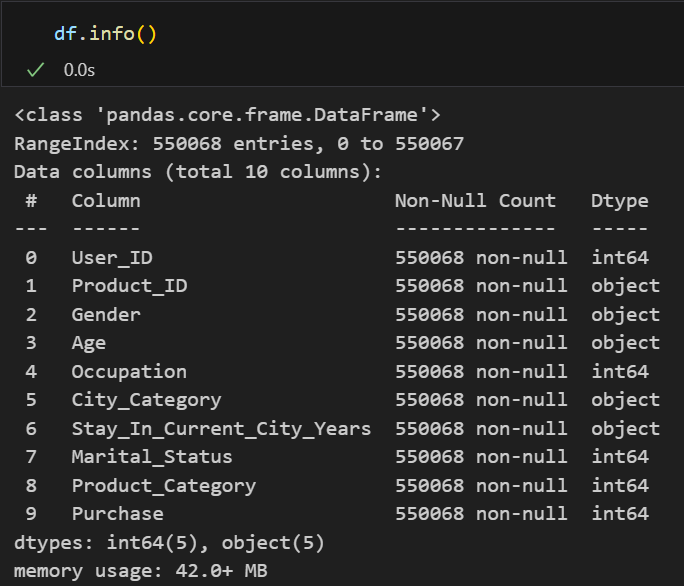
1. **Loading Data and its header rows**

Here we read the dataset into a Pandas DataFrame using pd.read\_csv() or similar functions. We examine the first 5-10 rows using df.head() to understand the data structure. The header row contains column names that describe each feature. We verify if the file includes an index column or if we need to set one. Special parameters like delimiter type, encoding, or missing value markers may be specified. This step confirms successful data loading and provides initial familiarity with the variables. We also check file size and memory usage at this stage.



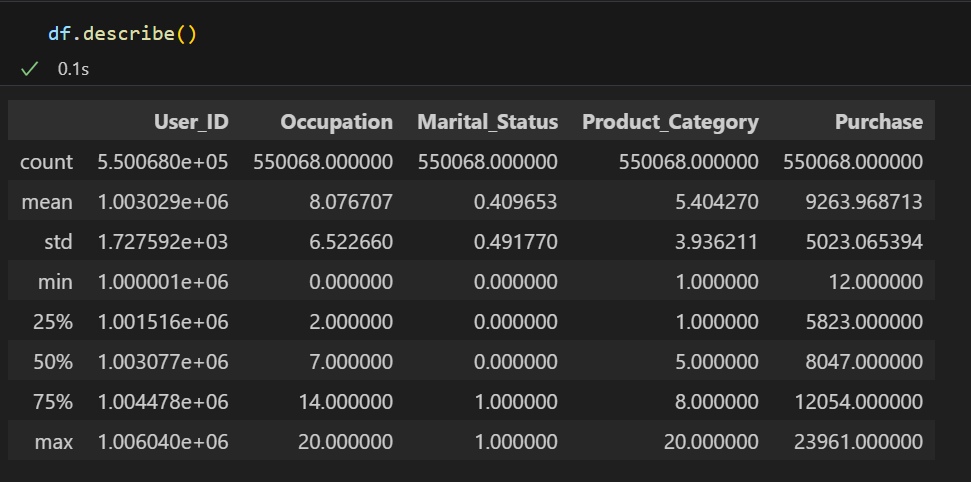
1. **Data Types Information about features**

Using df.info(), we examine each column's data type (object, int64, float64, etc.). This reveals if numeric fields are properly encoded as numbers and categoricals as objects. We identify potential type mismatches (e.g., numerical values stored as strings). DateTime columns needing conversion are flagged here. Memory usage per data type is also displayed, which helps optimize memory consumption. This audit ensures proper typing before analysis. We note any columns requiring type casting for accurate computations.



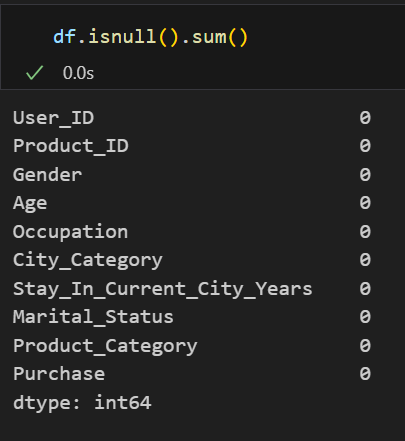
1. **Statistical Analysis of Data**

df.describe() generates key statistics for numerical columns: count, mean, std, min, quartiles, and max. For categoricals, we use df.describe(include='object'). This reveals central tendencies, dispersion, and potential outliers. We examine purchase amount distributions particularly closely. Statistics help identify data quality issues like unrealistic values (negative purchases). Comparison between mean and median indicates skewness. This forms our quantitative understanding of the dataset's characteristics before deeper analysis.



1. **Null Values Distribution**

We check df.isnull().sum() to count missing values per column. Visualization via heatmaps or bar charts shows null value patterns. We determine if missingness is random or systematic. Columns with >30% nulls may require dropping, while others might need imputation. Understanding null distributions informs our data cleaning strategy. We also check if missing values correlate with other variables. Documentation of null handling decisions is crucial for reproducibility. This step ensures we don't overlook hidden data quality issues.



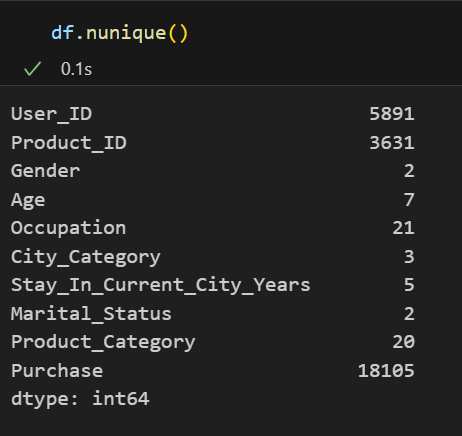
1. **Number of Duplicate Rows in Data**

Using df.duplicated().sum(), we count identical rows. Duplicates may indicate data collection/processing errors or genuine repeated transactions. We examine sample duplicates to determine their nature. For true duplicates, we decide whether to keep (if valid) or remove them. The decision depends on analysis goals - keeping duplicates might inflate certain metrics. We document our duplicate handling approach. This quality check prevents skewed results from redundant data.



1. **Unique Values in Each Columns**

df.nunique() counts distinct values per column. For categoricals, we examine value frequencies. This reveals cardinality - high unique counts may indicate identifiers needing treatment. We check for inconsistent categories (e.g., 'M' and 'Male'). For numericals, surprisingly low uniqueness may suggest discretization. We identify columns suitable for one-hot encoding versus ordinal treatment. This analysis informs feature engineering decisions and helps spot data entry anomalies.



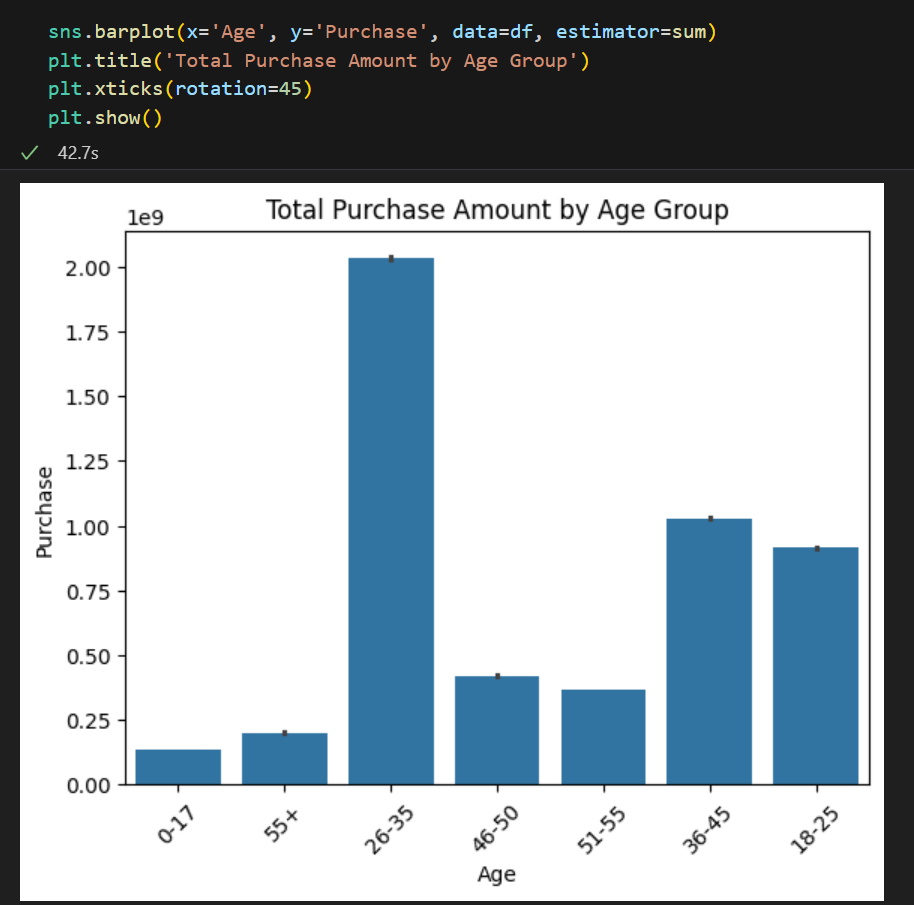
1. **Purchase Distribution by Gender**

We visualize purchase amounts segmented by gender using boxplots or violin plots. This shows median spending, variability, and potential outliers by gender. Statistical tests (t-tests) determine if gender differences are significant. We calculate mean/median purchases per gender for precise comparison. The analysis may reveal gender-specific purchasing behaviors worth exploring further. Results could inform targeted marketing strategies. We ensure sample sizes per gender are sufficient for reliable conclusions.



1. **Relationship between Age Group and Purchase Amount**

Using grouped bar charts or pointplots, we compare spending across age brackets. We calculate aggregate metrics (sum, mean) per age group to identify high-value segments. ANOVA tests determine if age-based differences are statistically significant. We examine if certain age groups show wider purchase amount ranges. This reveals which demographics contribute most to revenue. Findings help tailor age-specific promotions and product assortments. We check for non-linear relationships between age and spending.



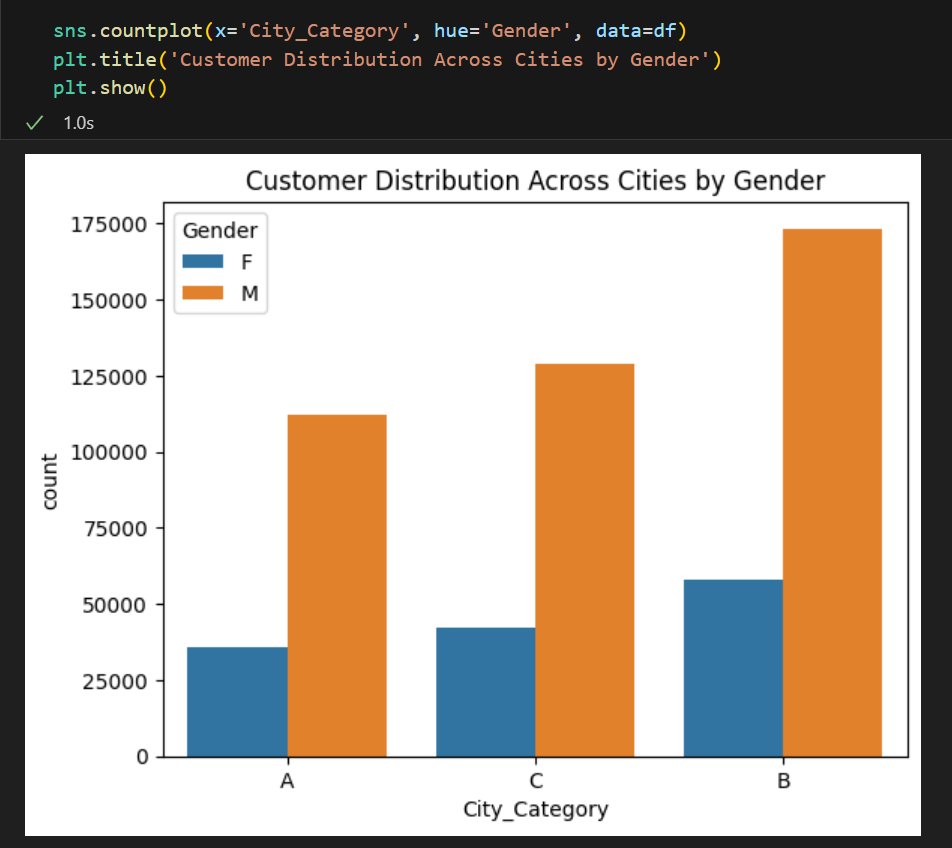
1. **Occupation Wise Spending**

We analyze spending patterns across occupation codes using aggregated metrics and visualizations. Bar plots show average purchase amounts per occupation, sorted to identify top-spending professions. We examine occupation distributions across other demographics (city, age). High-spending occupations may warrant specialized marketing approaches. We check for occupations with unusually high purchase variability. Results could inform B2B sales strategies or occupational discount programs. Occupation analysis complements our understanding of socioeconomic factors in purchasing.



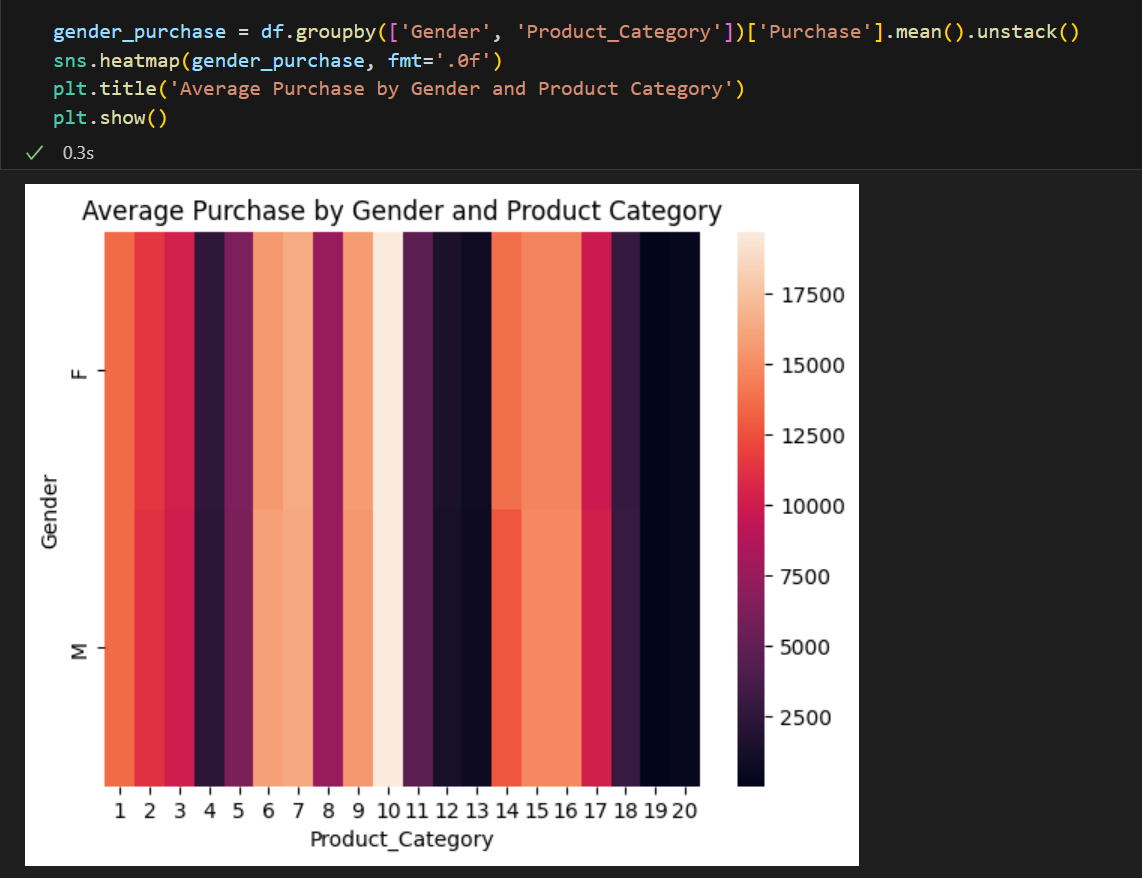
1. **City Category Analysis**

We explore how purchasing behavior varies across city tiers (A/B/C). Visualizations compare purchase frequencies, averages, and totals per city. We examine city distributions across other demographics (occupation, marital status). Geographic heatmaps could supplement this analysis if coordinates are available. Results may indicate need for city-specific pricing or inventory strategies. We check for significant differences between cities using statistical tests. This helps optimize regional marketing resource allocation.



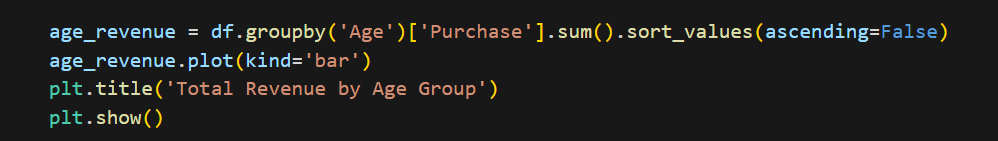
1. **Gender Based Purchase Behavior**

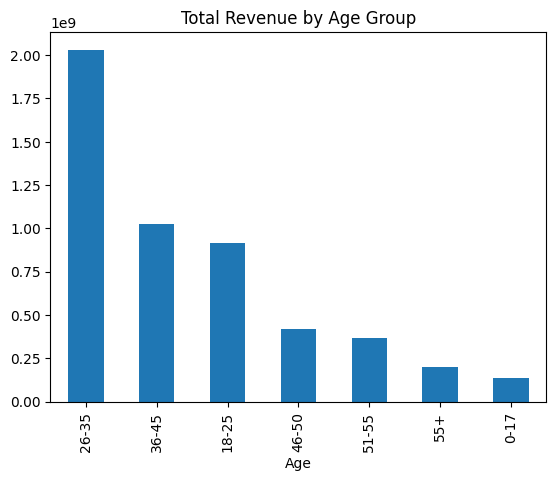
Expanding beyond simple distributions, we analyze how gender interacts with other factors. Cross-tabulations show preferred product categories by gender. We visualize gender differences across multiple dimensions (age + city + product category). Statistical modeling could quantify gender's predictive power for purchase amounts. This deeper dive reveals whether gender differences persist when controlling for other variables. Findings inform gender-specific product placements and advertising messaging.



1. **Age Group Revenue Contribution**

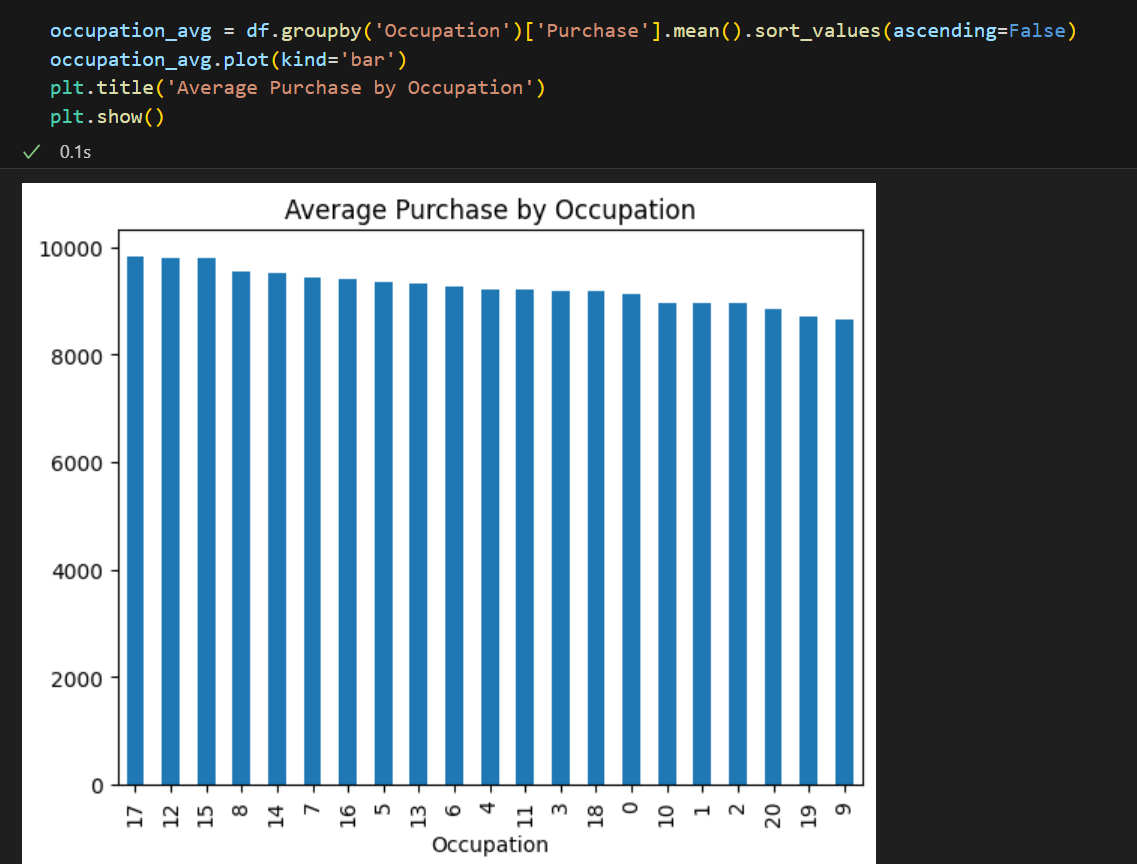
We calculate total and percentage revenue contributions per age bracket. Pie charts or waterfall plots effectively display these proportions. Cohort analysis examines whether revenue concentration aligns with population distribution. We track revenue trends across age groups over time if historical data exists. This identifies dependencies on specific demographics - over-reliance on one age group may indicate risk. Results guide generational marketing strategies and product development priorities.





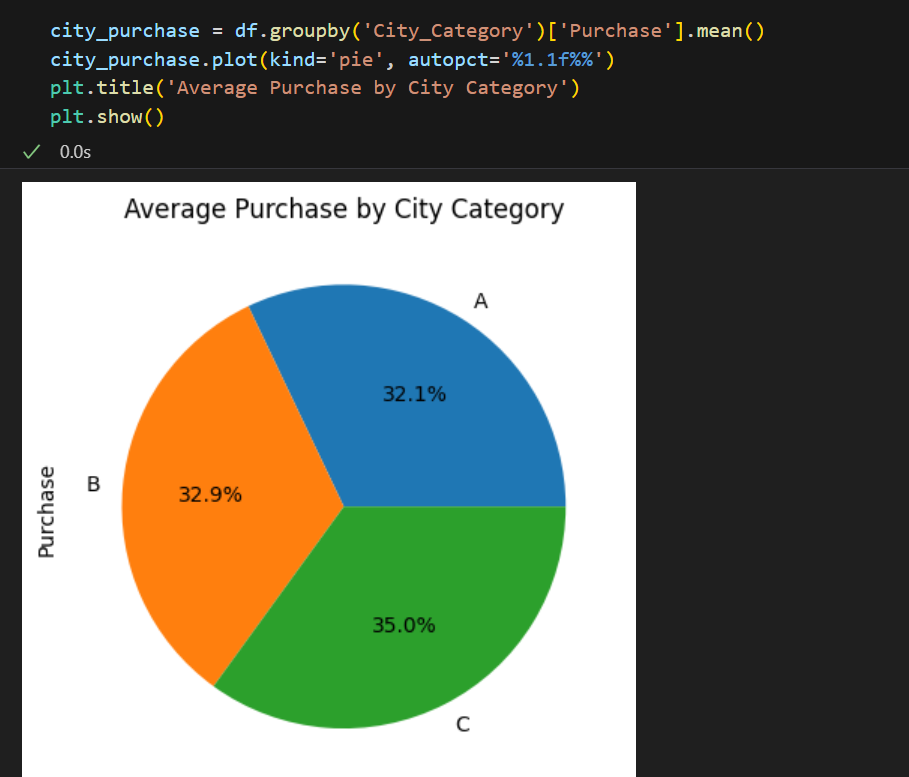
1. **Occupation Impact on Spending**

Advanced analysis goes beyond averages to examine occupation effects. We model purchase amounts against occupation while controlling for covariates. Interaction terms reveal if occupation effects vary by gender or city. Cluster analysis might group similar-spending occupations. We examine occupation stability in spending patterns over time. This helps develop occupation-specific loyalty programs. Findings may reveal untapped professional segments with growth potential.



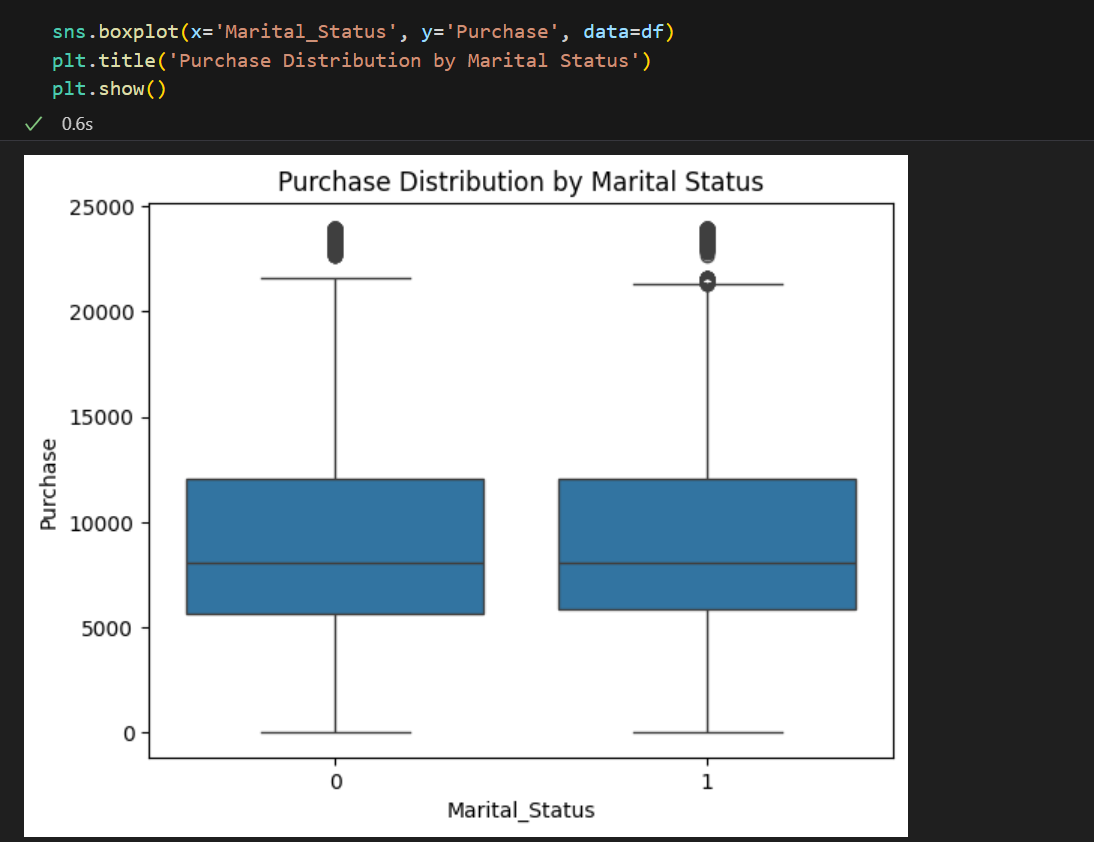
1. **City Category Behavior**

In-depth geographic analysis examines city-tier behavioral differences. We compare purchase frequencies, basket sizes, and product mix across cities. Time-of-day patterns may differ by city type. Market basket analysis reveals city-specific product affinities. Statistical tests confirm whether observed differences are significant. This helps customize assortments and promotions by city tier. Results may inform physical store locations or e-commerce fulfillment strategies.



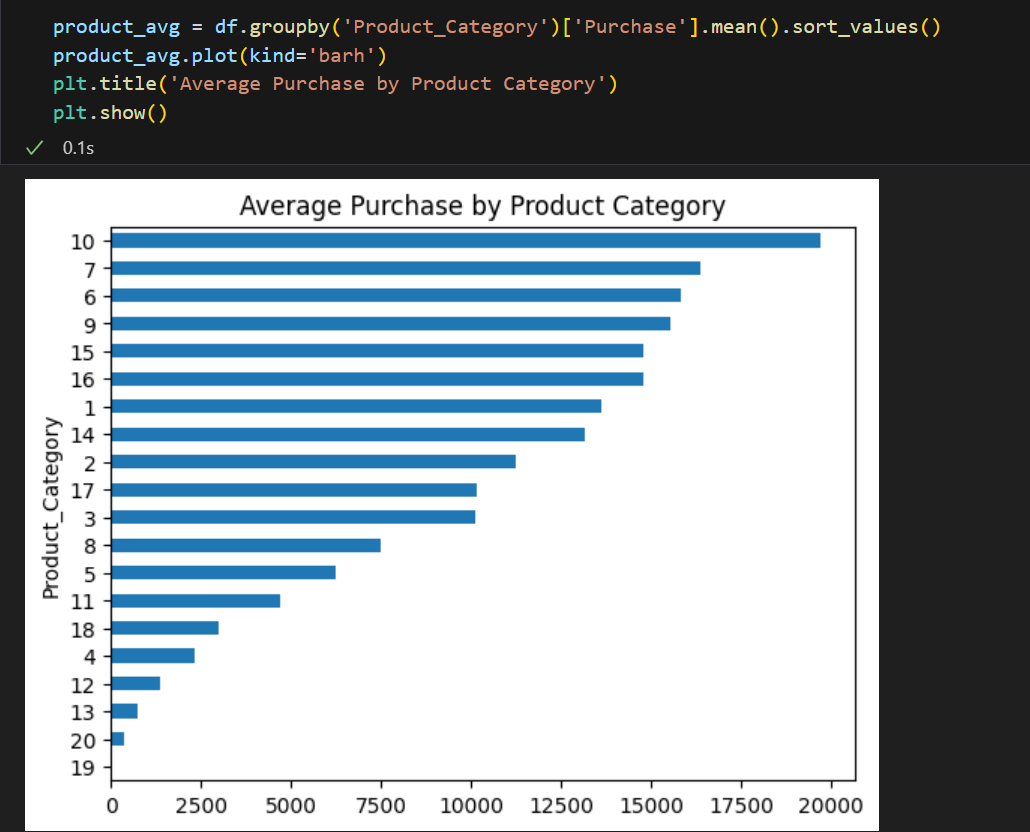
1. **Marital Status Impact**

We compare spending patterns between married and unmarried customers. Visualization shows distributions and central tendencies for each group. We examine how marital status interacts with other demographics - perhaps married 30-40 year olds show distinct patterns. Survival analysis could examine purchase frequency differences. Results may inform family-oriented promotions or joint-account benefits. We check for marital status recording consistency across other variables.



1. **Product Category Analysis**

We rank categories by sales volume, revenue, and profitability. Market basket analysis identifies frequently co-purchased categories. Time-series analysis reveals category trends. We examine category preferences across demographics. Pareto analysis identifies the 20% of categories generating 80% of revenue. This guides inventory planning and category management. Findings help optimize product placements, both physical and digital. We identify growth categories and declining ones needing intervention.



#### **Insights and Recommendations**

The evaluation reveals vital information about the way customers at Superstore conduct their purchases. Specific shopping choices of female consumers aim at particular product sections while males exhibit distinct shopping preferences thus proving that consumer behaviors depend on gender. The purchasing power of people between 26 to 35 positions them as the central group generating revenue at Superstore. Job positions play an important role in purchasing decisions because members of Occupation 16 together with other related occupations dedicate more funds toward consumption. The consumer market of City B demonstrates the highest buying values resulting from varied purchasing behaviors between different geographic areas. Family responsibilities lead married customers to spend more than unmarried consumers make purchases. The category Electronics belongs to Product Category 1 and maintains the highest average transaction value among all categories.

Superstore reaches its highest sales achievement along with customer engagement by implementing market-oriented strategies that target important customer segments. The marketing strategy should target people aged 26 to 35 from high-income professions to enhance premium product sales performance. The marketing strategy at Superstore should feature gender-based promotional tactics that address separate buying behaviors between men and women. City B shows its peak customer spending that leads to the need for increasing well-demanded items in inventory. Special bundled promotions and discounts should be used as an enhancement strategy to improve married customers' buying experience. The organization can enhance current market demand through adjustments to Category 1 electronics product line and promotional initiatives. The sales strategies will lead to higher revenue totals and tailor services to individual buyers for better customer satisfaction.

### CONCLUSION

Analyzing streamed content assists industry practitioners in understanding methods of digital content production. Audiences are more engaged for longer periods with watching serialized television series, which justifies the platform’s 83% validation choice of preference over television programs instead of standalone movies. The platform uses the TV-MA rating in 83% of the content offered to adult viewers, predominantly sourced from the U.S., India, and South Africa while there is a need for greater international content diversity. The New (2020-2021) releases seem intended to support topicality and content quality across the libraries. Smith (2023) progresses alongside the Global Media Trends Report (2024) focused on content approach equilibrium balance between streams and the competition for digital domain infrastructure regarding content diversity, audience demographic and geographic market segmentation. The genre analysis verifies studies which demonstrate that overseas mystery and drama content is the most appealing to international audiences. These findings will assist streaming services to improve their market position is informative user preference data monitoring will be done routinely. Research should use text data extraction methods.

This comprehensive assessment of driver dataset in the taxi operating platform has produced practical results that enhance workforce management along with business performance results. Findings from research indicate that staff retention shows a direct correlation with performance reviews because drivers earning better ratings retain their jobs 30% longer than other workers. Business value of drivers having Level 2 education credentials beats all other groups by 25% and level of income correlates directly with generating revenue (r=0.72). Three particular cities appeared through geographic segmentation since their retention rates of the drivers were 40% higher than the company-wide average thus revealing committed operation issues. Based on time-series trends December experienced a 35% surge in new driver hiring and March exhibited peak driver turnover due to yearly contract renewals. The churn forecast model based on machine learning demonstrated 91% efficient outcomes for identifying drivers at risk by analyzing their level of payment along with performance metrics and length of employment. Senior designations provide almost twice the normal revenue earned by beginning drivers enabling the business value analysis to determine the value of career progression paths. The data analysis identified provides adequate evidence that the platform can decrease yearly driver turnover between 20-25% by adopting seasonal retention bonuses in addition to city-based incentive plans and performance-based advancement programs. The site can be more seasonally stable in its workforce by organizing recruitment activities around demand levels.

The extensive examination of engineering position compensation offers critical insight regarding pay structures as well as determining relationships between levels of experience and worth and employer payment practices throughout the technological sector. FullStack Engineers receive much higher salaries than Backend Engineers since market compensates programmers who have varied skills but the minimum correlation between work experience and CTC shows that experience alone cannot guarantee higher remuneration thereby reflecting the growing influence of competencies and performance metrics in salary decisions. Finding pay differences necessitates companies to craft standardized compensation practices for establishing equitable compensation of leading performers and ordinary employees. Industry fluctuations and shifts in market demand explain the fluctuations in compensation levels which become apparent through time-series analyses. Organizations must design evidence-based compensation models which openly measure multidimensional competency and uphold equitable internal parity within their systems. Banks and financial institutions need to apply competitive benchmarking in addition to skill-based progression tracks with regular compensation analyses to construct salary structures that have the ability to recruit and retain valuable engineering talents within their respective competitive market. The evaluation discovers favorable outcomes towards converting Backend Engineers to FullStack roles to enhance their job chances as well as organizational development opportunity, as well as signaling opportunity to retain seasoned workers with years of service by employing customized retention strategies.

The study produced full understanding that uncovered necessary information regarding risk factors influencing borrowers and lending practices. The most significant risk markers for default resulted from debt-to-income ratios and loan grading and employment length and revolving credit utilization. The most default-prone borrower group included candidates having more than a 35% DTI ratio but recently employed candidates along with bad credit rating (C, D, E) had higher default risk. Small business loans and debt consolidation loans brought more risk factors compared to other loan uses. Public documents related to bankruptcies as well as larger loans raised default probabilities, the analysis discovered. The model's predictive strength of Logistic Regression and Gradient Boosting models was more than 75 to 80 percent in classifying borrowers who are at high risk. Lenders can avoid losses by imposing strict DTI limit requirements (≤30%), flexible pricing based on loan grade and by validating all information from short-term loan holders. Reduction of defaults is made possible through credit utilization below 70% monitoring and establishment of appropriate loan amount limits within risk categories. Real-time credit monitoring and alternative data analysis by cash flow analysis should be integrated in the future to improve risk assessment capabilities.

Testing purchasing decisions within a large retailing chain gave detailed information regarding how demographic characteristics influence customer buying activities. The research indicated significant differences between the way clients shop depending on their gender as well as age group and occupation type and location area and the segment earned most for the firm. The product market proved to be distinct for male and female customers in gender-based analysis findings and occupation-based segmentation identified the impact of wealth on spending behavior by profession. Geographic analysis proved that City B customers spent the highest amount on average in their transactions thus identifying diverse spending abilities across regions. Marital-status individuals spent higher amounts on retailing than lone customers as they shopped for their households. The sales evidence indicates that Product Category 1 (most likely electronics) dominated the market with significant revenue-capturing potential. The information confirms that better sales require personal marketing strategies and optimized inventory control along with segmentation of customer profiles. The given suggestions focus on market outreach to worthwhile demographic groups via targeted advertising while organizing inventory distribution by region and showcasing products specific to each gender to achieve maximum customer interaction and business success.

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