Store Trend Prediction

A data mining related application.

Building and Launching the Application

- Please go to Setting_Up_Venv.md to learn how to set up the virtual environment for this project. Follow the instructions to install all necessary packages. This project requires the Anaconda distribuition of Python.
- After configured correctly navigate to the the main directory of the project. You can then begin to run the main.py script which contains the KNN portion of the project.
- Also run Random_Forest.py to run the random forest portion of the application.
- Make sure directories are correct as paths may change.

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Introduction

Problem Statement

In all industries, it is important to understand the target consumers to maximize profits and sales. Consumer data is crucial for analyzing and identifying trends. Consumers exhibit certain tendencies based on their location, and companies need to comprehend which products they are inclined to purchase. Additionally, understanding the profitability of each purchase is essential to identify the most lucrative sales. This application utilizes multiple algorithms to achieve this. It uses KNN classification to pinpoint targeted cities and predict profits within the dataset. In addition to this, it uses random forest to determine the profit of each sale.

Objective

This application aims to predict the likelihood of a city purchasing a product from an office store, such as furniture and work supplies. It further classifies the profits associated with each purchase and identifies the specific products contributing to those profits. By discerning which products are frequently purchased in specific cities and understanding the profit margins, companies can tailor their sales strategies more effectively. The application is developed using the Anaconda distribution for Python, which incorporates various machine learning packages.

Motivation

This project is motivated by the need to simulate a real-world data mining application that involves collaborative teamwork and extensive knowledge within the field. Understanding consumer data is crucial for companies seeking insights into consumer behavior. The application provides valuable information on what products a company can expect its consumers to purchase and the associated profits. Furthermore, gaining a deep understanding of the algorithms, processes, and techniques used in this application is essential knowledge for the developers.

Related Work

Several related topics align with this application, including retail analytics, market basket analysis, geospatial analysis, customer segmentation, predictive modeling, and collaborative filtering. The project draws inspiration from techniques in retail analytics and predictive modeling. Similar projects involve determining average sales per order, identifying valuable consumers, and optimizing product orders based on location.

Data

Data Source and Format

The dataset is sourced from Sample Super Store and is presented in an Excel format (.xls). This dataset comprises 9,994 purchases from various cities in the United States and Canada. Key features include category, product name, sales, quantity, discount, and profit. The primary label for the application is the city. The dataset incorporates numerical, categorical, and ordinal features, with a focus on numerical and categorical features for efficient model training. The sample data, consisting of around 10,000 entries, allows for robust experimentation.

Data Example

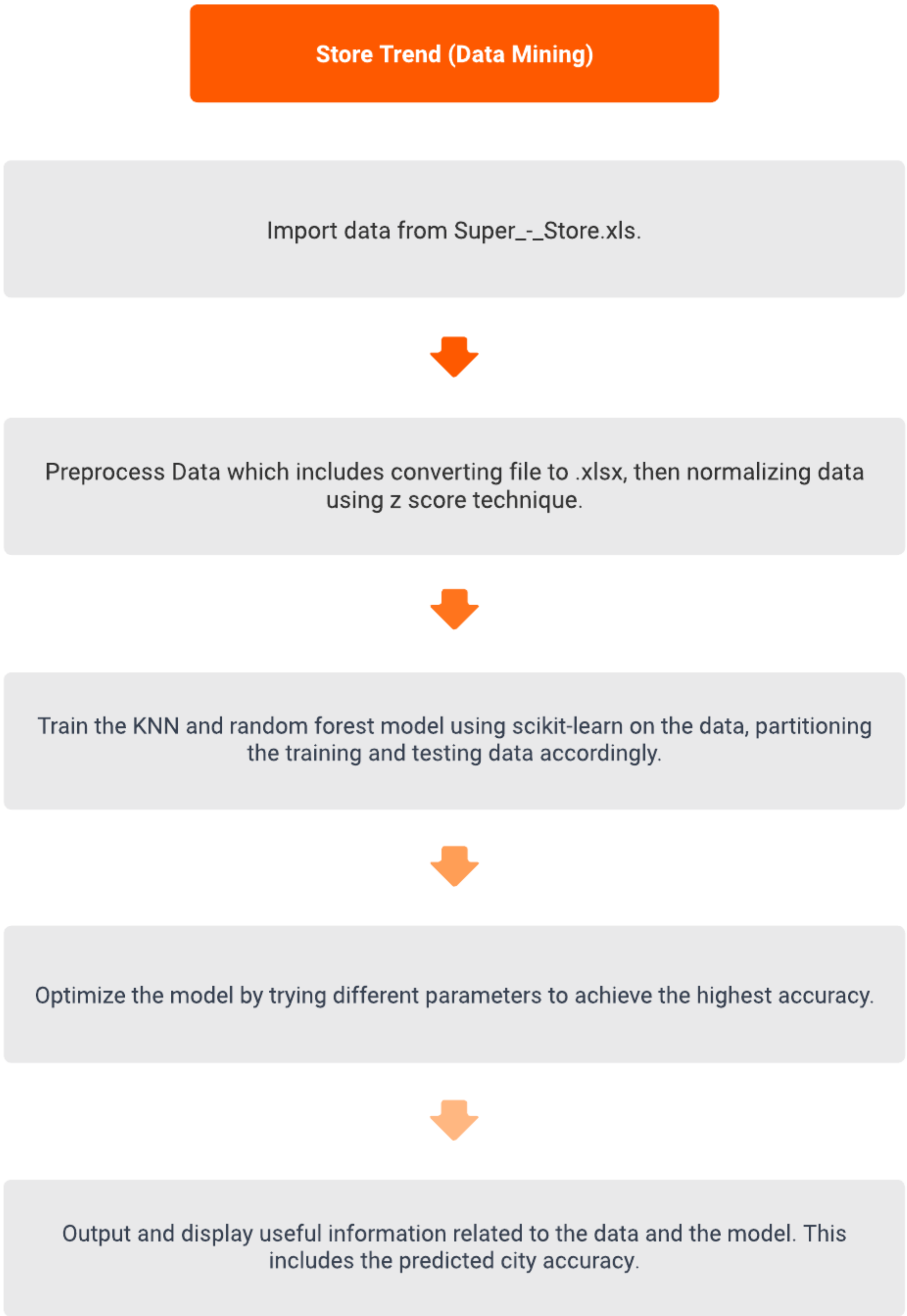
Below is an excerpt from the dataset before the preprocessing steps:

Row ID	Order ID	Order Date	Ship Date	Ship Mode	Customer ID	Customer Name	Segment	Country	City	State	Postal Code	Region	Product ID	Category	Sub-Category	Product Name	Sales	Quantity	Discount	Profit
1	CA-2016-152156	11/8/2016	11/11/2016	Second Class	CG-12520	Claire Gute	Consumer	United States	Henderson	Kentucky	42420	South	FUR-BO-10001798	Furniture	Bookcases	Bush Somerset Collection Boc	261.96	2	0	41.9136
2	CA-2016-152156	11/8/2016	11/11/2016	Second Class	CG-12520	Claire Gute	Consumer	United States	Henderson	Kentucky	42420	South	FUR-CH-10000454	Furniture	Chairs	Hon Deluxe Fabric Upholstere	731.94	3	0	219.582
3	CA-2016-138688	6/12/2016	6/16/2016	Second Class	DV-13045	Darrin Van Huff	Corporate	United States	Los Angeles	California	90036	West	OFF-LA-10000240	Office Suppli	Labels	Self-Adhesive Address Labels f	14.62	2	0	6.8714
4	US-2015-108966	10/11/2015	10/18/2015	Standard Class	SO-20335	Sean O'Donnell	Consumer	United States	Fort Lauderd	Florida	33311	South	FUR-TA-10000577	Furniture	Tables	Bretford CR4500 Series Slim R	957.5775	5	0.45	-383.031
5	US-2015-108966	10/11/2015	10/18/2015	Standard Class	SO-20335	Sean O'Donnell	Consumer	United States	Fort Lauderd	Florida	33311	South	OFF-ST-10000760	Office Suppli	Storage	Eldon Fold 'N Roll Cart System	22.368	2	0.2	2.5164
6	CA-2014-115812	6/9/2014	6/14/2014	Standard Class	BH-11710	Brosina Hoffman	Consumer	United States	Los Angeles	California	90032	West	FUR-FU-10001487	Furniture	Furnishings	Eldon Expressions Wood and I	48.86	7	0	14.1694
7	CA-2014-115812	6/9/2014	6/14/2014	Standard Class	BH-11710	Brosina Hoffman	Consumer	United States	Los Angeles	California	90032	West	OFF-AR-10002833	Office Suppli	Art	Newell 322	7.28	4	0	1.9656
8	CA-2014-115812	6/9/2014	6/14/2014	Standard Class	BH-11710	Brosina Hoffman	Consumer	United States	Los Angeles	California	90032	West	TEC-PH-10002275	Technology	Phones	Mitel 5320 IP Phone VoIP pho	907.152	6	0.2	90.7152
9	CA-2014-115812	6/9/2014	6/14/2014	Standard Class	BH-11710	Brosina Hoffman	Consumer	United States	Los Angeles	California	90032	West	OFF-BI-10003910	Office Suppli	Binders	DXL Angle-View Binders with L	18.504	3	0.2	5.7825
10	CA-2014-115812	6/9/2014	6/14/2014	Standard Class	BH-11710	Brosina Hoffman	Consumer	United States	Los Angeles	California	90032	West	OFF-AP-10002892	Office Suppli	Appliances	Belkin F5C206VTEL 6 Outlet Su	114.9	5	0	34.47
11	CA-2014-115812	6/9/2014	6/14/2014	Standard Class	BH-11710	Brosina Hoffman	Consumer	United States	Los Angeles	California	90032	West	FUR-TA-10001539	Furniture	Tables	Chromcraft Rectangular Confe	1706.184	9	0.2	85.3092
12	CA-2014-115812	6/9/2014	6/14/2014	Standard Class	BH-11710	Brosina Hoffman	Consumer	United States	Los Angeles	California	90032	West	TEC-PH-10002033	Technology	Phones	Konftel 250 Conference phone	911.424	4	0.2	68.3568
13	CA-2017-114412	4/15/2017	4/20/2017	Standard Class	AA-10480	Andrew Allen	Consumer	United States	Concord	North Carolir	28027	South	OFF-PA-10002365	Office Suppli	Paper	Xerox 1967	15.552	3	0.2	5.4432
14	CA-2016-161389	12/5/2016	12/10/2016	Standard Class	IM-15070	Irene Maddox	Consumer	United States	Seattle	Washington	98103	West	OFF-BI-10003656	Office Suppli	Binders	Fellowes PB200 Plastic Comb	407.976	3	0.2	132.5922
15	US-2015-118983	11/22/2015	11/26/2015	Standard Class	HP-14815	Harold Pawlan	Home Office	United States	Fort Worth	Texas	76106	Central	OFF-AP-10002311	Office Suppli	Appliances	Holmes Replacement Filter fo	68.81	5	0.8	-123.858
16	US-2015-118983	11/22/2015	11/26/2015	Standard Class	HP-14815	Harold Pawlan	Home Office	United States	Fort Worth	Texas	76106	Central	OFF-BI-10000756	Office Suppli	Binders	Storex DuraTech Recycled Pla	2.544	3	0.8	-3.816
17	CA-2014-105893	11/11/2014	11/18/2014	Standard Class	PK-19075	Pete Kriz	Consumer	United States	Madison	Wisconsin	53711	Central	OFF-ST-10004186	Office Suppli	Storage	Stur-D-Stor Shelving, Vertical 5	665.88	6	0	13.3176
18	CA-2014-167164	5/13/2014	5/15/2014	Second Class	AG-10270	Alejandro Grove	Consumer	United States	West Jordan	Utah	84084	West	OFF-ST-10000107	Office Suppli	Storage	Fellowes Super Stor/Drawer	55.5	2	0	9.99
19	CA-2014-143336	8/27/2014	9/1/2014	Second Class	ZD-21925	Zuschuss Donatelli	Consumer	United States	San Francisco	California	94109	West	OFF-AR-10003056	Office Suppli	Art	Newell 341	8.56	2	0	2.4824
20	CA-2014-143336	8/27/2014	9/1/2014	Second Class	ZD-21925	Zuschuss Donatelli	Consumer	United States	San Francisco	California	94109	West	TEC-PH-10001949	Technology	Phones	Cisco SPA 501G IP Phone	213.48	3	0.2	16.011
21	CA-2014-143336	8/27/2014	9/1/2014	Second Class	ZD-21925	Zuschuss Donatelli	Consumer	United States	San Francisco	California	94109	West	OFF-BI-10002215	Office Suppli	Binders	Wilson Jones Hanging View Bi	22.72	4	0.2	7.384
22	CA-2016-137330	12/9/2016	12/13/2016	Standard Class	KB-16585	Ken Black	Corporate	United States	Fremont	Nebraska	68025	Central	OFF-AR-10000246	Office Suppli	Art	Newell 318	19.46	7	0	5.0596
23	CA-2016-137330	12/9/2016	12/13/2016	Standard Class	KB-16585	Ken Black	Corporate	United States	Fremont	Nebraska	68025	Central	OFF-AP-10001492	Office Suppli	Appliances	Acco Six-Outlet Power Strip, 4	60.34	7	0	15.6884
24	US-2017-156909	7/16/2017	7/18/2017	Second Class	SF-20065	Sandra Flanagan	Consumer	United States	Philadelphia	Pennsylvania	19140	East	FUR-CH-10002774	Furniture	Chairs	Global Deluxe Stacking Chair,	71.372	2	0.3	-1.0196
25	CA-2015-106320	9/25/2015	9/30/2015	Standard Class	EB-13870	Emily Burns	Consumer	United States	Orem	Utah	84057	West	FUR-TA-10000577	Furniture	Tables	Bretford CR4500 Series Slim R	1044.63	3	0	240.2649
26	CA-2016-121755	1/16/2016	1/20/2016	Second Class	EH-13945	Eric Hoffmann	Consumer	United States	Los Angeles	California	90049	West	OFF-BI-10001634	Office Suppli	Binders	Wilson Jones Active Use Binde	11.648	2	0.2	4.2224
27	CA-2016-121755	1/16/2016	1/20/2016	Second Class	EH-13945	Eric Hoffmann	Consumer	United States	Los Angeles	California	90049	West	TEC-AC-10003027	Technology	Accessories	Imation 8GB Mini TravelDrive	90.57	3	0	11.7741
28	US-2015-150630	9/17/2015	9/21/2015	Standard Class	TB-21520	Tracy Blumstein	Consumer	United States	Philadelphia	Pennsylvania	19140	East	FUR-BO-10004834	Furniture	Bookcases	Riverside Palais Royal Lawyers	3083.43	7	0.5	-1665.0522
29	US-2015-150630	9/17/2015	9/21/2015	Standard Class	TB-21520	Tracy Blumstein	Consumer	United States	Philadelphia	Pennsylvania	19140	East	OFF-BI-10000474	Office Suppli	Binders	Avery Recycled Flexi-View Cov	9.618	2	0.7	-7.0532
30	US-2015-150630	9/17/2015	9/21/2015	Standard Class	TB-21520	Tracy Blumstein	Consumer	United States	Philadelphia	Pennsylvania	19140	East	FUR-FU-10004848	Furniture	Furnishings	Howard Miller 13-3/4" Diame	124.2	3	0.2	15.525
31	US-2015-150630	9/17/2015	9/21/2015	Standard Class	TB-21520	Tracy Blumstein	Consumer	United States	Philadelphia	Pennsylvania	19140	East	OFF-EN-10001509	Office Suppli	Envelopes	Poly String Tie Envelopes	3.264	2	0.2	1.1016
32	US-2015-150630	9/17/2015	9/21/2015	Standard Class	TB-21520	Tracy Blumstein	Consumer	United States	Philadelphia	Pennsylvania	19140	East	OFF-AR-10004042	Office Suppli	Art	BOSTON Model 1800 Electric	86.304	6	0.2	9.7092
33	US-2015-150630	9/17/2015	9/21/2015	Standard Class	TB-21520	Tracy Blumstein	Consumer	United States	Philadelphia	Pennsylvania	19140	East	OFF-BI-10001525	Office Suppli	Binders	Acco Pressboard Covers with	6.858	6	0.7	-5.715
34	US-2015-150630	9/17/2015	9/21/2015	Standard Class	TB-21520	Tracy Blumstein	Consumer	United States	Philadelphia	Pennsylvania	19140	East	OFF-AR-10001683	Office Suppli	Art	Lumber Crayons	15.76	2	0.2	3.546
35	CA-2017-107727	10/19/2017	10/23/2017	Second Class	MA-17560	Matt Abelman	Home Office	United States	Houston	Texas	77095	Central	OFF-PA-10000249	Office Suppli	Paper	Easy-staple paper	29.472	3	0.2	9.9468
36	CA-2016-117590	12/8/2016	12/10/2016	First Class	GH-14485	Gene Hale	Corporate	United States	Richardson	Texas	75080	Central	TEC-PH-10004977	Technology	Phones	GE 30524EE4	1097.544	7	0.2	123.4737

Methodology

Schematic Diagram/Framework

The application's structure and processes are depicted in the following schematic diagram:



Data Visualization and Preprocessing

Data preprocessing involved several steps to prepare the dataset for model training. Firstly, the.xls file was converted to.xlsx to meet the updated format requirements of Pandas. Normalization was then performed using the minimum-maximum and Z_score normalization techniques. This involved scaling specific columns, such as sales, quantity, discount, and profit, to a range between 0 and 1, ensuring uniformity for effective model training. At first, we used the minimum-maximum normalization technique, but the scaling didn't come out correctly. For example, $-300 of profit and $20 of profit all have the same scaling value, which doesn't seem correct. Then we normalize the data using the Z-Score technique. The scaling looks correct when the profit is high, showing a positive value that is above 0, which means it is above the average profit, and when the profit is super low, it shows a negative value below 0, which means it is below the average profit or even negative. So we decided to use the Z-Score technique.

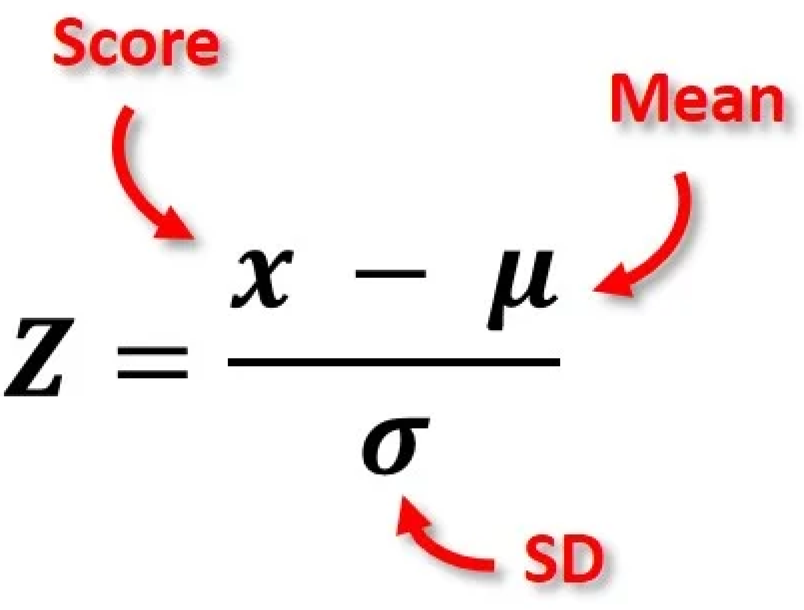
Normalization Technique

$$X_{\text{normalized}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

Where:

- X is the original data point.
- $X_{\min}$ is the minimum value of the feature in the dataset.
- $X_{\max}$ is the maximum value of the feature in the dataset.
- $X_{\text{normalized}}$ is the normalized value of X within the range [0, 1].

Z-Score Technique



Procedures and Features

The methodology employed in this project encompasses several key procedures and features. The initial step involves exploratory data analysis (EDA) to gain insights into the distribution and relationships within the dataset. Following this, feature selection is conducted to identify the most influential variables for model training. Features such as city, category, sub-category, sales, quantity, discount, and profits are crucial for predicting consumer behavior and profitability.

The algorithm applied was the K-Nearest Neighbors (KNN) classification algorithm, Random Forest Regression, and Random Forest Classification

The original algorithm utilized is the K-Nearest Neighbors (KNN) classification algorithm. KNN identifies patterns based on the similarity of instances, making it suitable for predicting city preferences and associated profits and sub-categories. Additionally, feature scaling techniques are applied to ensure that no single feature dominates the model training process. But the result and the accuracy didn't come out great; the best accuracy we can get is 22% even with the parameter tuning. In order to increase accuracy we changed the number of columns included into kNN algorithm. Instead of using single column, we started using eleven columns. Then tested with the applied Random Forest Classification algorithm with the same features (profits and sub-categories) and target (city), the accuracy only increased by about 10%, which still didn't meet expectations.

Second, we decided to change our features and target to see if we could get better accuracy and training scores as well. The feature we focused on was subcategory, category, sales, quantity, and target profit using the random forest regression algorithm. The result is still not good because the profit is a continuous value, regression doesn’t perform well at around 50% accuracy, and the training score is 83%. Then we categorized the profit into high, low, and negative for-profit and used the same feature and a random forest classifier model to predict the result, which came out so much better for profit. In the categorization, if the value is greater than $200, the profit is set to be high, under $200-$0, and negative if the value is less than $0. The accuracy was able to get up to 87%, and the training score was 89%. We discussed the result with the team members, and we applied the "discount" column to our features as well. The result is surprisingly great; the accuracy went up to 95% and the training score went up to 99.6%

Experiments

Data Division (Training/Testing)

To assess the model's performance accurately, the dataset is divided into training and testing sets. Approximately 80% of the data is allocated for training, allowing the model to learn patterns, while the remaining 20% is reserved for testing to evaluate its predictive capabilities. Stratified sampling is implemented to maintain the distribution of feature sets, ensuring representative training and testing subsets.

Parameter Tuning

Parameter tuning is a critical aspect of optimizing the KNN and Random Forest models.

KNN:

- The selection of the optimal number of neighbors (K) is crucial for the model's accuracy. A systematic approach, such as cross-validation, is employed to iterate through various K values and identify the configuration that yields the best results. K was set to 200.

- Random state parameters in machine learning algorithms, including the KNN and Random Forest classifiers, serve as a seed for the random number generator used by the algorithm. This parameter is used to ensure reproducibility. When you provide an integer value for a random state, it makes the output of the algorithm deterministic, meaning that you can expect the same results in multiple runs of the algorithm with the same input data and parameter settings. Random State was set to 42 in KNN Classifier.

- Weights: This parameter determines how the classification is weighted when making a prediction. The options are typically 'uniform' (where all points in each neighborhood are weighted equally), 'distance' (where points are weighted by the inverse of their distance, so closer neighbors have a greater influence), or a custom function. Weights was set to 'uniform'.

- Algorithm: This specifies the algorithm used to compute the nearest neighbors. Options include 'ball_tree', 'kd_tree', 'brute', and 'auto'. The 'auto' option attempts to decide the most appropriate algorithm based on the values passed to fit method. Algorithm was set to 'auto'.

- leaf_size: This parameter can affect the speed of the construction and query, as well as the memory required to store the tree. The leaf size is passed to the BallTree or KDTree algorithms. In general, it does not affect the actual results, but it can impact the speed of the query and the memory required to store the constructed tree. Leaf_size was set to 30.

- p: This parameter is related to the choice of metric; when p = 1, this is equivalent to using manhattan_distance (l1), and euclidean_distance (l2) for p = 2. For arbitrary p, minkowski_distance (lp) is used. It effectively determines the power parameter for the Minkowski metric. p value was set to 2.

- Metric: This determines the distance metric used for the tree. The default metric is minkowski, and with p=2 is equivalent to the standard Euclidean metric. Other common options include 'euclidean', 'manhattan', 'chebyshev', 'hamming', 'canberra', and 'braycurtis', or any other valid distance metric supported by scipy.spatial.distance. Metric was set to 'euclidean' distance method.

Random Forest Classifier

- Random state parameters in machine learning algorithms, including the KNN and Random Forest classifiers, serve as a seed for the random number generator used by the algorithm. This parameter is used to ensure reproducibility. When you provide an integer value for a random state, it makes the output of the algorithm deterministic, meaning that you can expect the same results in multiple runs of the algorithm with the same input data and parameter settings. Random State was set to 100 in RF Classifier.
- N_estimators serve in Random Forest classifier is the number of trees in the forest. Typically, the more trees, the better the performance, but it also means a longer training time. N_Estimators was set to 250.
- Max_depth serve The maximum depth of each tree. Deeper trees can model more complex patterns but can also lead to overfitting. Max depth of the tree was set to 20.

Evaluation Metrics

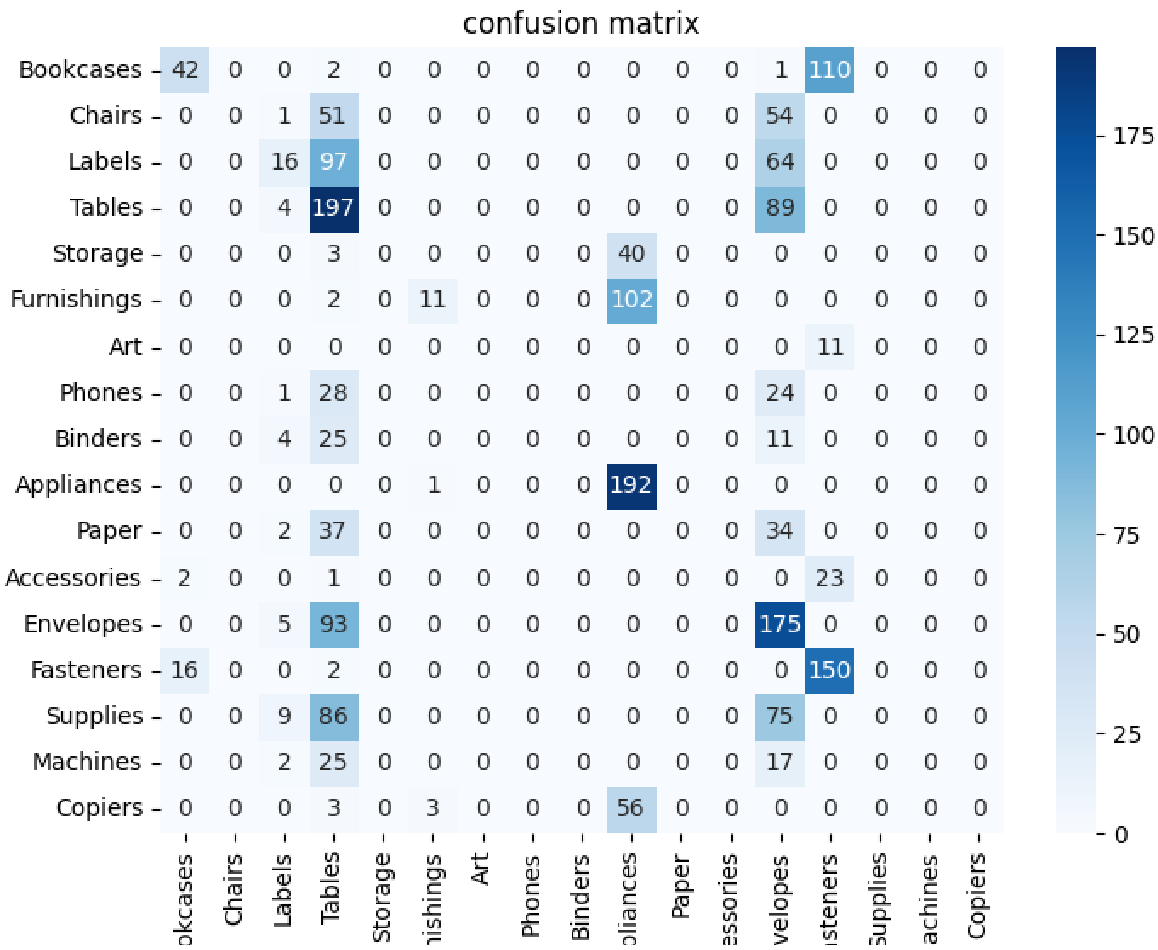
The performance of the model is evaluated using several metrics, including accuracy, precision, recall, and F1-score. Accuracy provides an overall measure of the model's correctness, while precision and recall offer insights into the model's ability to predict positive instances correctly and capture all positive instances, respectively. The F1 score combines precision and recall, providing a balanced assessment of the model's performance.

Results (Tables and Graphs)

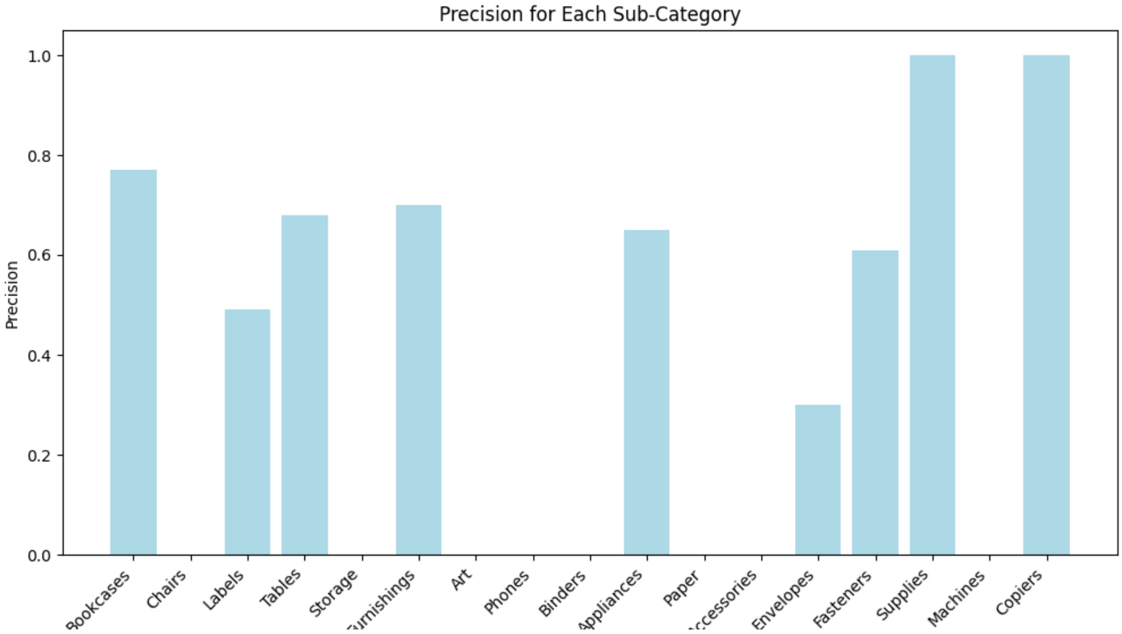
KNN Model

Here we can see the graphs related to the KNN algorithm training results.

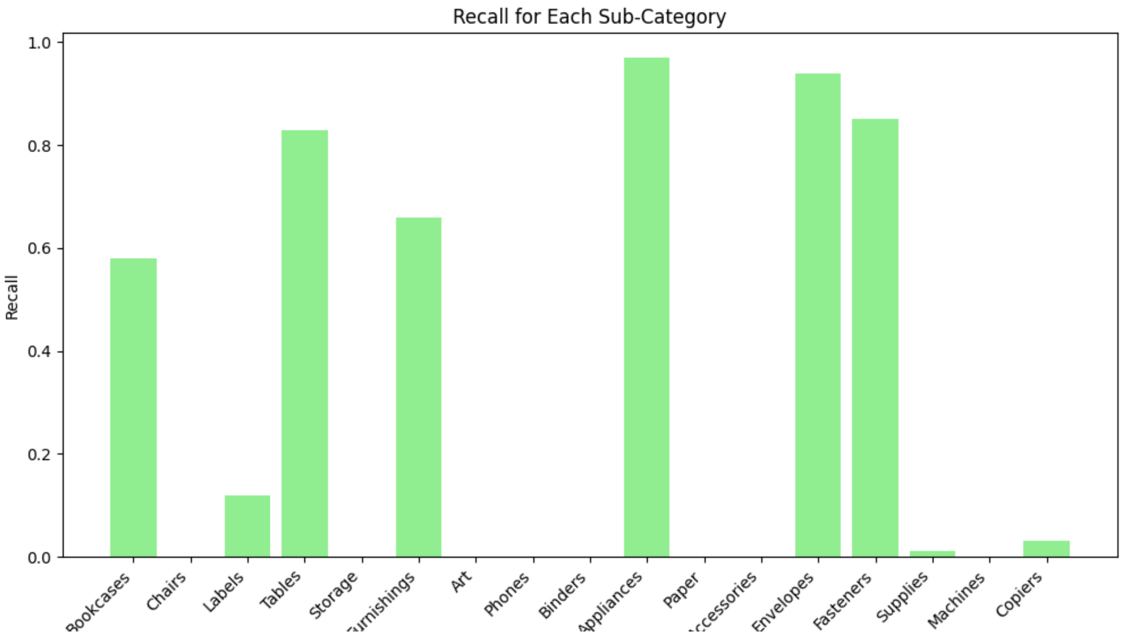
Confusion matrix for KNN



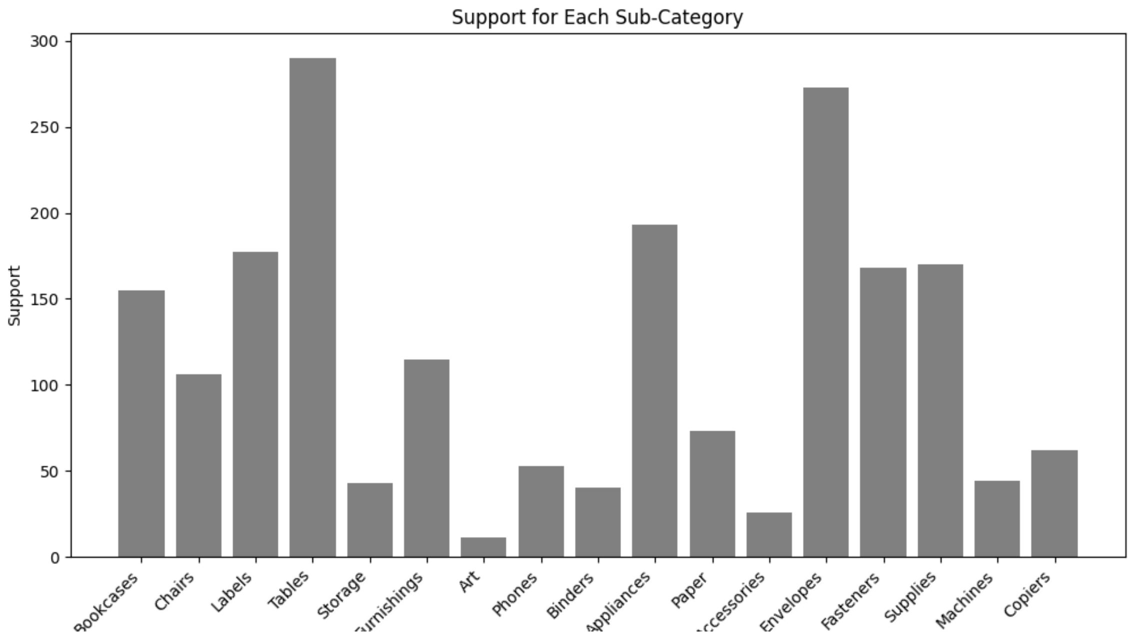
Precision for KNN



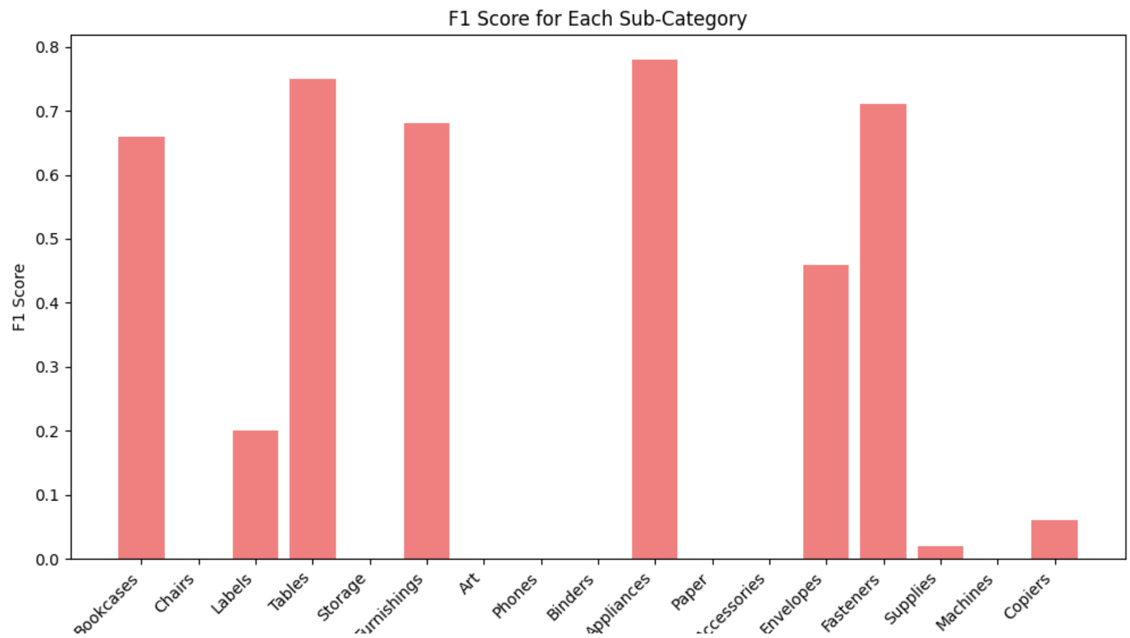
Recall for KNN



Support for KNN



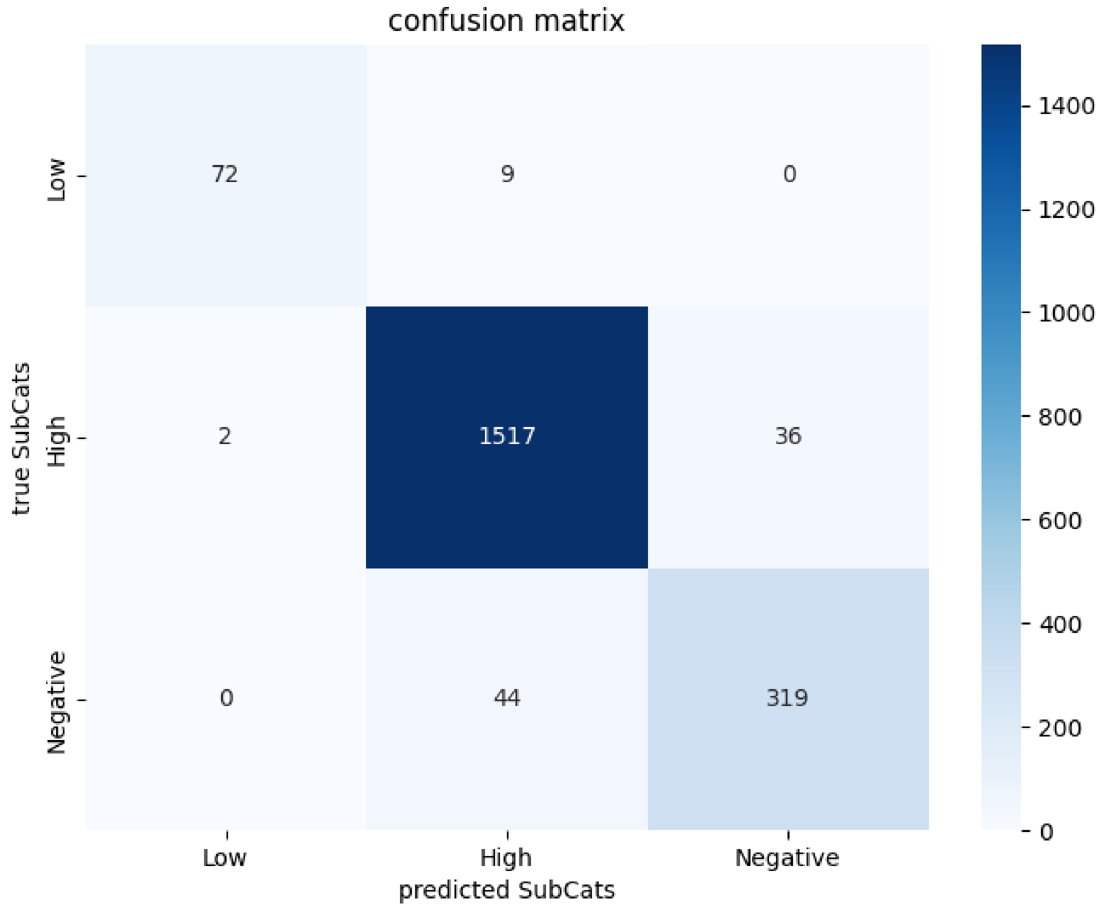
F1 Score KNN



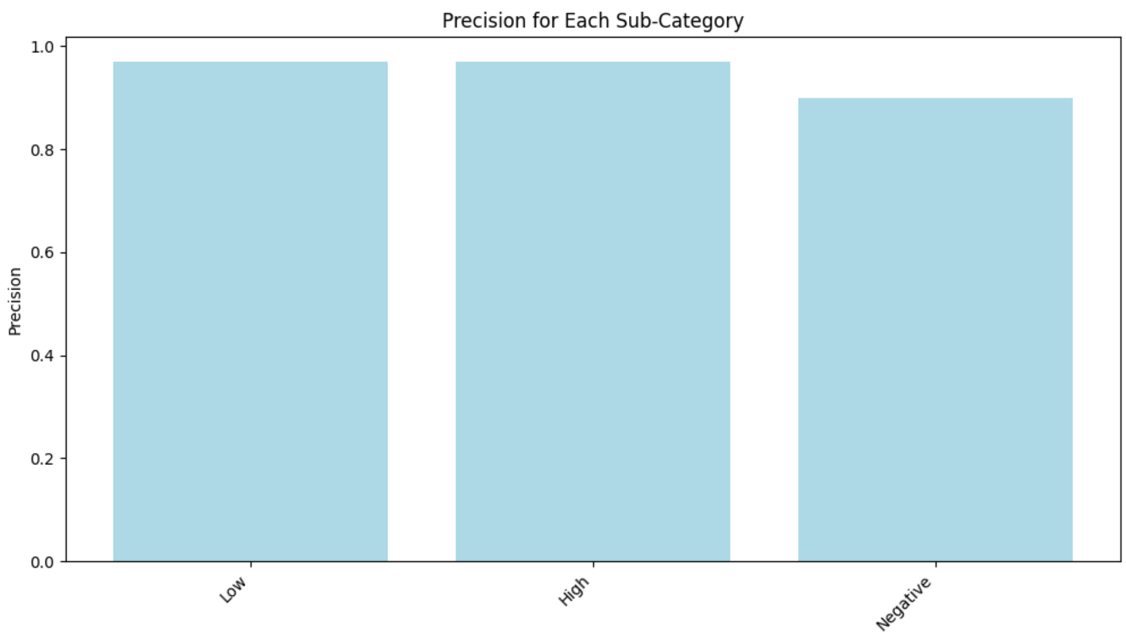
Random Forest Model

And below we can see the graphs related to the Random Forest algorithm training results.

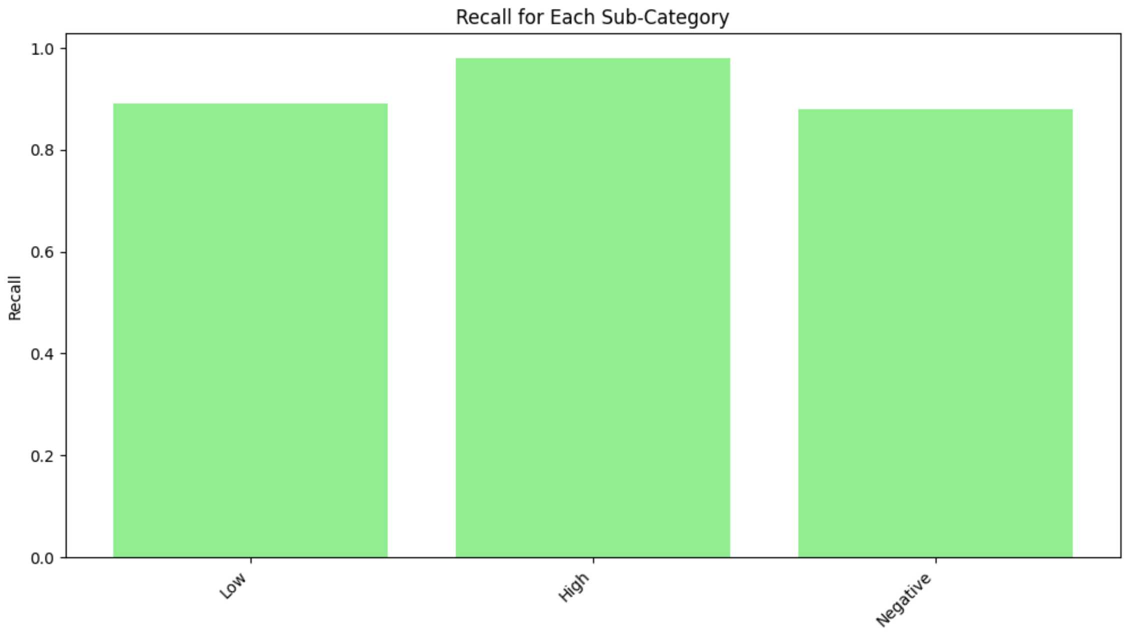
Confusion matrix for Random Forest



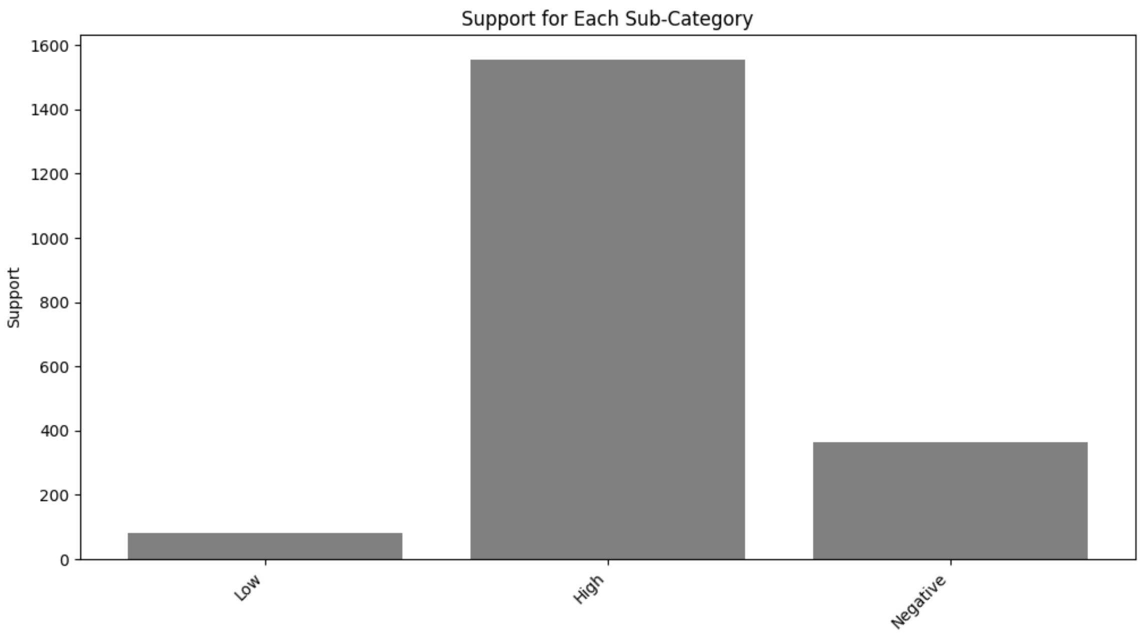
Precision for Random Forest



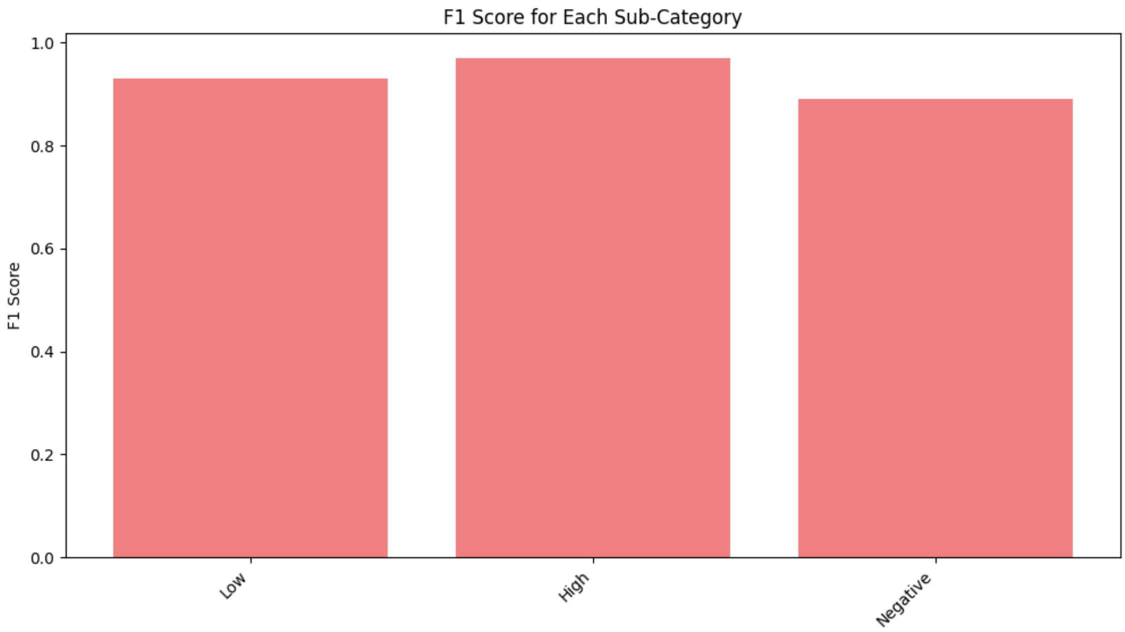
Recall for Random Forest



Support for Random Forest



F1 Score Random Forest



The results of the experiments are presented in the form of tables and graphs. A confusion matrix is generated to visualize the model's performance in predicting city preferences and associated profits.

Analysis of the Results

The analysis of results involves interpreting the metrics and visualizations to draw meaningful conclusions. Insights are gained into which cities exhibit similar purchasing behavior, the most profitable products in specific regions, and any patterns that may guide strategic business decisions. Any discrepancies between predicted and actual outcomes are thoroughly investigated to understand potential areas for improvement.

Conclusion

Discuss Any Limitation

Despite the model's success in predicting city preferences and profits, certain limitations exist. The model assumes that consumer behavior remains constant over time, and external factors, such as economic changes or global events, are not considered. Additionally, the dataset's geographical scope is limited to the United States and Canada, potentially limiting the model's applicability to a broader international context.

Discuss Any Issue Not Resolved

One unresolved issue pertains to the interpretability of the model's decisions. While the model can make accurate predictions, understanding the underlying reasons for specific predictions remains a challenge. Further research into interpretable machine learning techniques may address this issue.

Future Direction

Future work could involve enhancing the model's predictive capabilities by incorporating more sophisticated machine learning algorithms, such as ensemble methods or neural networks. Additionally, expanding the dataset to include a more diverse set of regions and demographics would contribute to a more comprehensive understanding of consumer behavior. Collaboration with domain experts in retail and data science could provide valuable insights and further refine the model.

References

- Anaconda Python Distribution - Anaconda | The World’s Most Popular Data Science Platform
- KNN Classifier sklearn.neighbors.KNeighborsClassifier — scikit-learn 1.3.2 documentation
- Random Forest sklearn.ensemble.RandomForestClassifier — scikit-learn 1.3.2 documentation