ALY6040

DATA MINING APPLICATIONS

MODULE 6 FINAL PROJECT REPORT

TEAM 3:

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Introduction

Overview of Dataset

We are using the "Google Play Store Applications" dataset collected in June 2021 in our final project. The initial dataset had 2,312,944 entries and 24 features.

Data Dictionary

Target Variable (y)	**Description**	**Type**
In-App Purchases	In-App purchases in-app (True/False)	Categorical
Feature Variables(x)	**Description**	**Type**
Free	Whether the app is Free or Paid (True/False)	Categorical
Developer ID	Developer ID in Google Playstore	Categorical
Ad Supported	Ad support in-app (True/False)	Categorical
Editors Choice	Whether rated as Editor Choice (True/False)	Categorical
Min Version	Minimum app support system version of Android	Categorical
Category	App Category	Categorical
Size	Size of the application package	Categorical
App Name	Name of the app	Categorical
App Id	Package name	Categorical
Developer Email	Email-id of developer	Categorical
Content Rating	The maturity level of the app	Categorical
Currency	The currency of the app price	Categorical
Rating	Average rating	Numerical
Rating Count	Number of rating(reviews)	Numerical
Installs	Approximate install count	Numerical
Minimum Installs	Approximate minimum app install count	Numerical
Maximum Installs	Approximate maximum app install count	Numerical
Price	App price	Numerical
Released	App launch year on Google Playstore	Numerical
Last Updated	Last app update year	Numerical
Developer Website	Website of the developer	URL
Privacy Policy	Privacy policy from the developer	URL

After reviewing the features of the initial dataset, we are curious about the availability and transparency of "*In-App Purchases*" and see the role it plays in shaping user preferences, app strategies, and the overall competitiveness and success of mobile applications in the market.

Use Cases

- Role: Software Investor
- Goal: Assists investors in identifying and leveraging the features of mobile apps that maximize their benefits.
- Approach: Identify the best model for maximizing your company's benefits by predicting whether or not an app has "in-app purchases," allowing investors to develop a more effective strategy for finding the apps with the highest ROI.

Model Selection

Given that our target variable, "In-App Purchase," and the majority of variables in the dataset are categorical values (True/False), we conducted three tree-based classifier models in this report.

- Random Forest Classifier
- Decision Tree Classifier
- Gradient Boosting Classifier

Metrics for Model Evaluation(Classification Model)

Based on the classification model, we apply several metrics to evaluate the model:

- Confusion Matrix
- Precision / Recall / F-1 Score
- Receiver Operating Characteristic Curve (ROC) and Area Under the Curve (AUC)
- Precision-Recall Curve

Precision is a crucial metric in this report. In the mobile app store market, the cost of false positives (predicting In-App purchases when they won't occur) is significant. Therefore, our prediction strategy focuses on minimizing false positives and ensuring accurate positive predictions to maximize profits from In-App purchases.

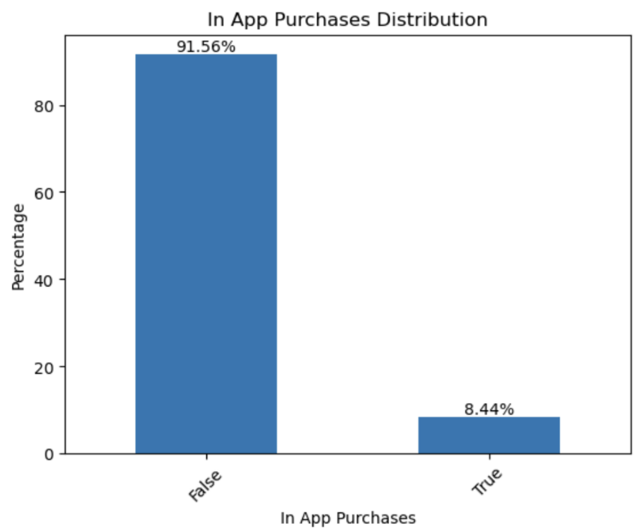
In contrast, the cost of false negatives (missed In-App purchases) is not high in our case, as we assume the cost of encouraging purchases is relatively low. Even if a purchase would have occurred naturally without our efforts, the additional cost is not substantial.

Data Resampling and Cleaning

Undersampling

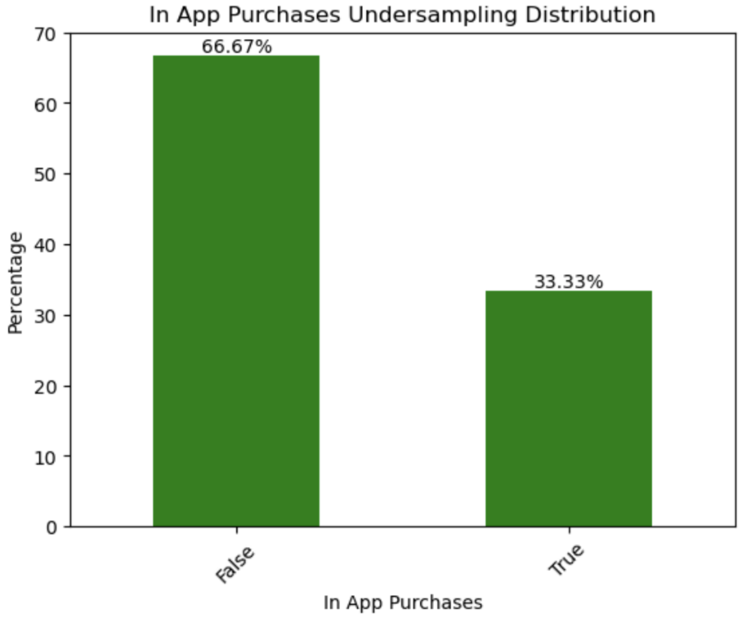
We first checked the data distribution of the target variable "In-App Purchases" and the variable contained the class imbalance issue. The percentage of "false" is 91.6%, significantly higher than the 8.44% of "true." Therefore, we resample the data by using undersampling.

Figure 1. In-App Purchase Distribution.



After the undersampling, we changed the proportion of "false" and "true" to 2:1. Since a specific percentage difference can accurately represent the real data distribution, we have chosen to retain some data imbalance and have not adjusted the ratio between the two categories to make them equal.

Figure 2. In-App Purchase Distribution After Undersampling.



Dropping Columns

We drop the columns that are highly unique or contain non-related information, such as URL or email address.

Variable	Dropping Reason
App Id	Highly unique
Developer Website	URL
Developer Email	Email address
Privacy Policy	URL
App Name	Highly Unique
Developer Id	Highly Unique
Scraped Time	All the same time in each row. (2021-06-16)

Missing Values

We examined the dataset for null values, and the table below displays the total count of missing values for each variable that contains null values.

Variable	Missing Value (entries)	Size of Missing Value
Installs	13	Light Delete less than 1% of the dataset.
Minimum Installs	13	
Currency	16	
Size	20	
Rating Count	3131	Heavy Be filled with averages values.
Rating	3131	
Minimum Android	856	Heavy Converted and filled with means.
Released	7979	

- Light Missing Value Processes:
    1) Remove rows with three or more null values = > "Minimum Installs", "Installs", and "Size" containing 0 null values. "Currency" only remains 1 null value.
    2) Drop the only null value of "Currency" = > "Currency" remains 0 null.
- Heavy Missing Value Processes:
    1) Impute the mean for null values. => "Rating", "Rating Count", "Released", and "Minimum Android" remain 0 null.

Data Transform and Imputation

The dataset contained complicated categorical data, and many columns required preprocessing to be used for analysis and modeling.

Extraction and Converting Data for Analysis

Variable	Transformation
Update Interval Days	We created a new column named “Update Interval Days” to calculate the version update cycle of the mobile application. Ex) Released = 2022-01-15 < Last Updated = 2023-09-16 Update Interval Days = (2023-09-16)-(2021-06-01) = 473 days
Min Version	Convert the original value to numerical value. Ex) 4.1 and up = > 4.1 3.2 - 7.1.1 = > 3.2 Varies with Device = > mean of total version
size_numeric(KB)	Convert the original value to numerical value. Ex) 11M = 11*1024 = 11,264 KB Varies with Device = > mean of total size (KB)

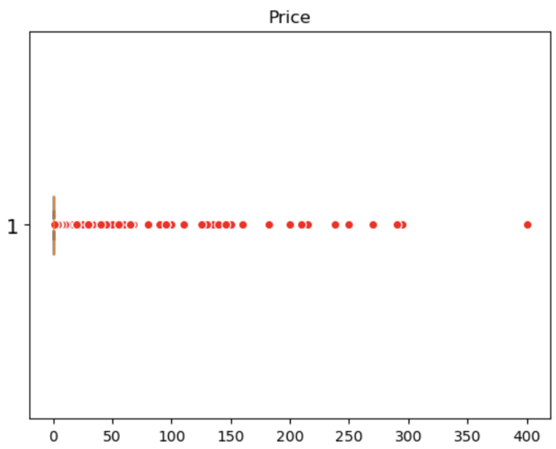
Data Encoding

We applied LabelEncoder() from sklearn to encode the categorical values.

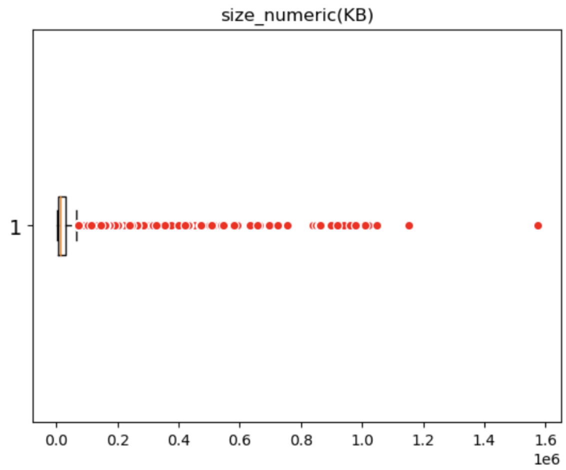
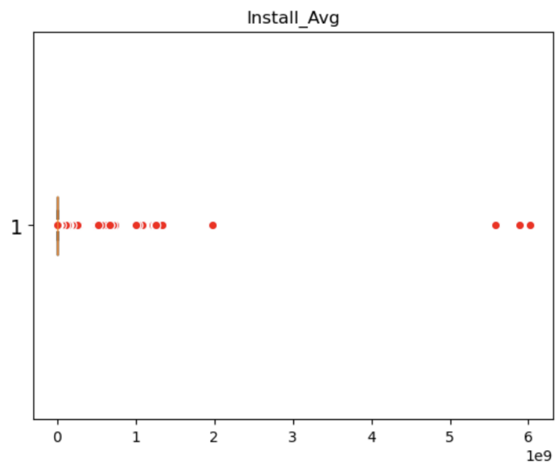
Variable	Encoding
Free Ad Supported In-App Purchases Editors Choice	Encode the values by 0, 1, 2, 3, etc….

Outlier

We check the outlier of numerical variables using IQR value and box plot.

<table>
<tr><th>Reserved Outlier</th><th>Reason</th></tr>
<tr><td>


</td><td>Because 0 accounts for 98% of the total data, the upper bound tends to be 0, making the paid data appear anomalous. We think this skewed fits the real world and we don't use price as a target variable. Therefore, I think we can leave the outlier here.</td></tr>
</table>

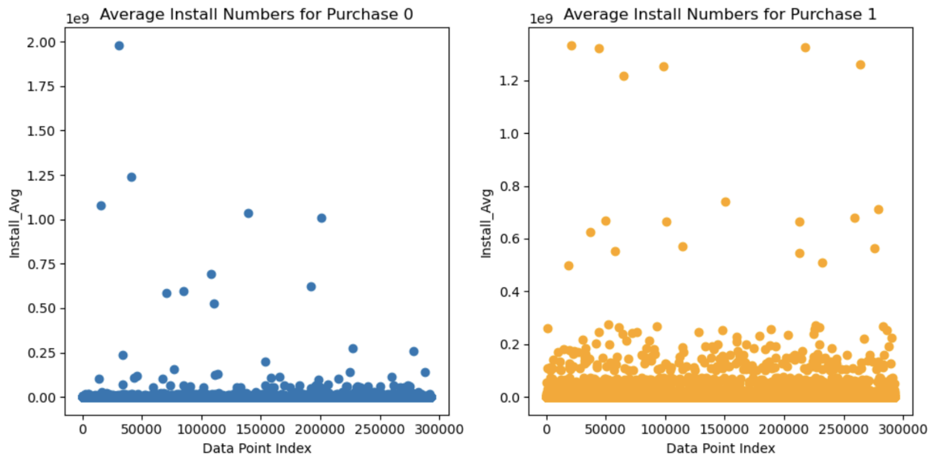
<table>
<tr>
<td></td>
<td>The outlier data aligns with real-world situations, and its maximum value is not outrageous. It contains valid information that cannot be easily deleted. Moreover, the number of outliers is not large compared to our overall data, so we are considering not handling them.</td>
</tr>
<tr>
<td>Fixed Otlier</td>
<td>Fixing Process</td>
</tr>
<tr>
<td></td>
<td>Install_Avg contained abnormal maximum values.
2155096 1.102881e+10
1773294 7.077124e+09
1060335 7.017202e+09
944254 6.962820e+09
2011395 6.204067e+09
Name: Install_Avg, dtype: float64
We checked the total downloads of Facebook, TikTok, and Instagram. Their total number of installations since launch is less than 5 billion. Therefore, we will delete values beyond 5 billion.
1429623 2.882165e+09
1628043 1.488313e+09
353242 1.384996e+09
2009528 1.325789e+09
65037 1.322906e+09
Name: Install_Avg, dtype: float64</td>
</tr>
</table>

Additionally, we only process the outliers in "Install_Avg" and retain outliers in other fields to accurately represent real-world app store installation situations.

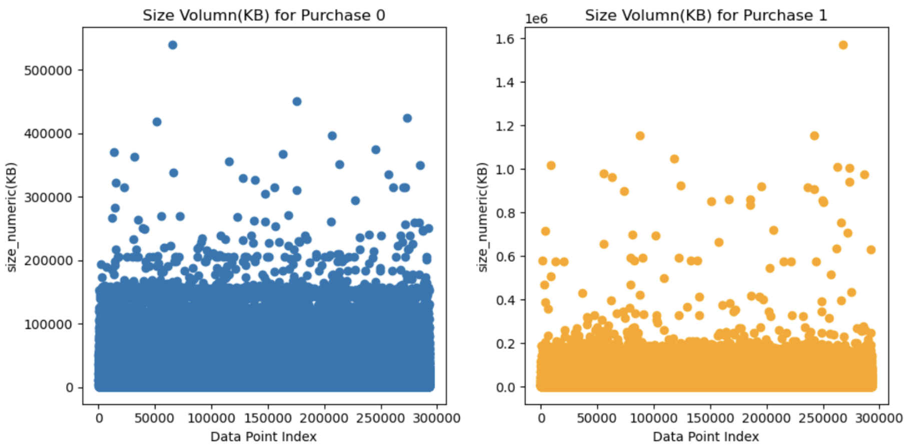
Exploratory Data Analysis

After initializing the data cleaning and imputation, we conducted an exploration of the variables.

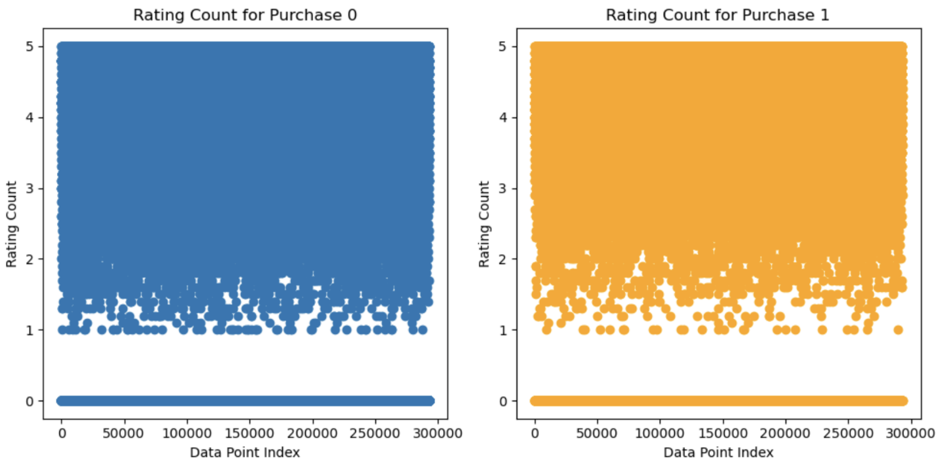
- "Install_Avg" and "In-App Purchases" relationship: When "In-App Purchases" is 0, the average "Install Avg" is significantly higher at 130,870, compared to 1,195,096 when "In-App Purchases" is 1.



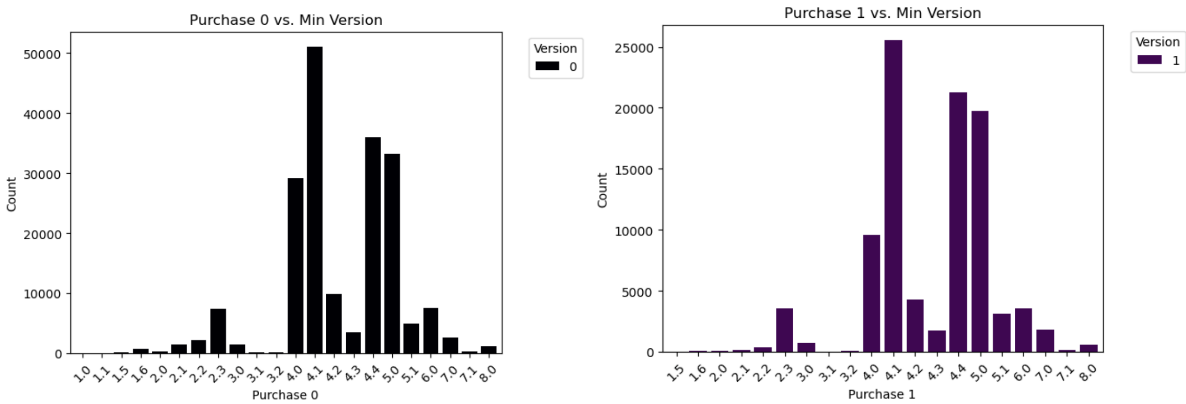
- "Size_numeric(KB)" and "In-App Purchases" relationship: Apps with "In-App Purchases" set to 1 have a larger average size of 34,122 compared to 18,781 for apps with "In-App Purchases" set to 0.



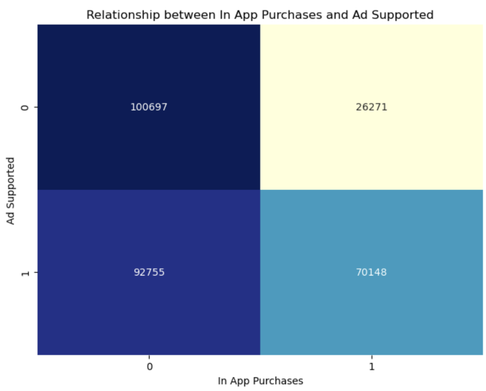
- "Rating Count" and purchase correlation: Apps with more rating counts are more likely to be purchased. When "In-App Purchases" is 0, the average "Rating Count" is 2.10, while it's 3.27 when "In-App Purchases" is 1.



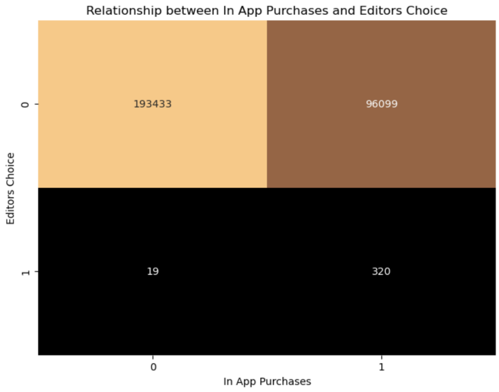
- Influence of "Min version": The average values are similar for different "In-App Purchases" values, but apps with "In-App Purchases" set to 1 tend to support slightly higher versions.



- Impact of “Ad Supported”: Approximately 56 percent of apps have advertisements, and those with ads have a purchase ratio of 43 percent, significantly higher than the 20 percent purchase rate for ad-free apps.



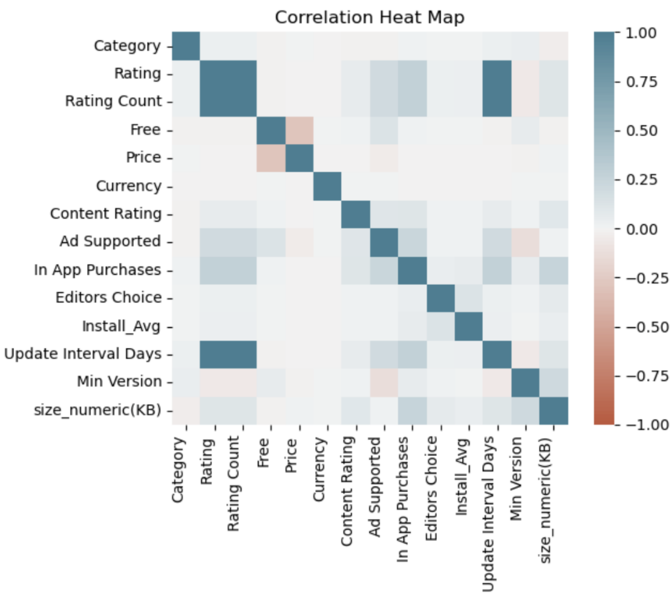
● "Editor's Choice" and purchase rate: Only 0.1 percent of apps are chosen by editors. For editor's choice apps, the purchase rate is 94 percent, while apps not chosen by editors have a 33 percent purchase rate.



● In the correlation heatmap, we find that " Update interval days", "Ratings" and "Rating Count" are strongly and positively correlated, with correlation coefficients close to 1.

● "In-App Purchases" is positively correlated with "Rating", "Rating Count", "Ad Support", "Update interval days" and "size_numeric(KB)" with a correlation around 0.25.

● "Price" and "Free" are negatively correlated with a correlation coefficient around -0.25.



In addition, we observed that when apps had a higher number of rating counts, they were more likely to be purchased.

Data Modeling Preprocessing

Target and Feature variables

Target Variable (y)	Feature Variable (X)		
"In-App Purchase": **To predict whether the app provides *In-App* purchases.** (True 1 /False 0)	Free	Whether the app is Free or Paid (True/False)	Categorical
	Ad Supported	Ad support in-app (True/False)	Categorical
	Editors Choice	Whether rated as Editor Choice (True/False)	Categorical
	Min Version	Minimum app support system version of Android	Categorical
	size_numeric	Size of application package	Numerical
	Rating	Average rating	Numerical
	Rating Count	Number of rating(reviews)	Numerical
	Installs	Approximate install count	Numerical
	Update Interval Days	The version update cycle of the mobile application.	Numerical
	Price	The price of the app.	Numerical
	Currency	0: USD, 1: XXX, 2: EUR, 3: INR, 4:SGD, 5: VND	Numerical
	Content Rating	Maturity level of app (1: everyone, 4: Teen, 3: Mature 17+, 2: Everyone 10+, 0: Adults only 18+, 5: Unrated)	Numerical

Data Splitting and Normalization

We imported the *train_test_split* function from *sklearn.model_selection* to randomly split the train and test datasets. Import *StandardScaler* from sklearn.preprocessing to normalize feature variables.

Train and Validation	Test	Normalization
Ratios: 80% of 202,909 entries. Dataset: X_train, y_train.	Ratios: 20% of 86,962 entries. Dataset: X_test, y_test.	Dataset: X_train_nor, X_test_nor

Random Forest Classifier

Hyperparameter Tunning (Cross Validation)

In hyperparameter tuning, we import the ***RandomizedSearchCV*** function from ***sklearn.model_selection*** to optimize the model's performance. We apply the best hyperparameter on the train datasets (X_train, y_train)

Best Parameters	Scoring
'n_estimators': 500 (The contribution of each tree to the final prediction) **'min_samples_split': 2** (The minimum number of samples required at a leaf node) **'min_samples_leaf': 5** (The minimum number of samples required to split an internal node) **'max_samples': 0.3** **'max_depth': 20**	**'Precision'**

Pairs of parameters were examined using cross-validation, and the best parameters were selected based on the 'Precision' score, which considers balanced model performance.

Model_Tuning (Controlling imBalance)

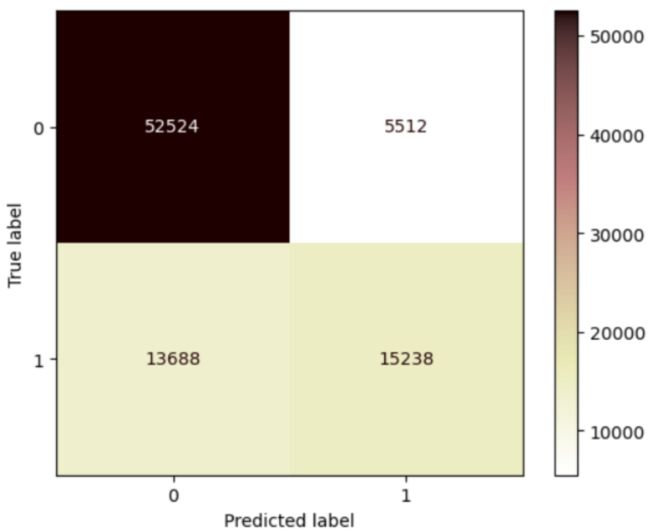
The target variable exhibited an imbalance, with the number of data points labeled as '1' constituting 33% of the total data, while '0' accounted for the rest. While the imbalance was not severe, we sought to enhance the model's performance by applying class weights and SMOTE (Synthetic Minority Over-sampling Technique).

After applying class weights and SMOTE, the F1 score improved; however, our primary metric of interest, 'precision,' did not exhibit the same improvement. As a result, we concluded that the basic Random Forest model, without any further tuning, performed best for our purposes.

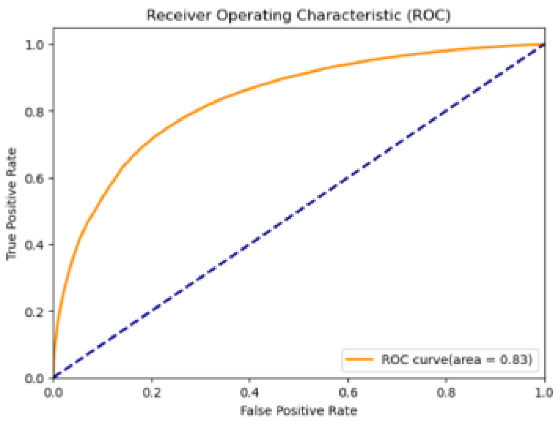
Basic Random Forest	***Random Forest_class_weight***	***Random_Forest_SMOTE***
(Precision) 0.73 *(Recall) 0.53* *(F1) 0.61*	*(Precision) 0.65* *(Recall) 0.69* *(F1) 0.67*	*(Precision) 0.66* *(Recall) 0.69* *(F1) 0.67*

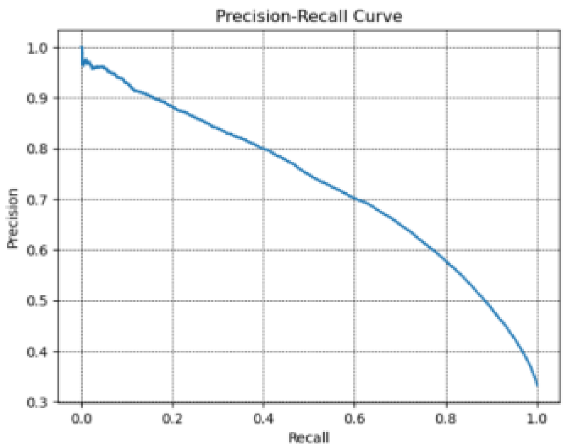
Model Evaluation

The best random forest model has a precision of 0.73, a recall of 0.53, and an F1-score of 0.61. Comparatively, higher precision and lower recall indicate a large number of False Negatives. As seen in the confusion matrix, there are 13,688 positives ('purchased') misclassified as negatives ('no purchased'). In comparison, the number of False Positives is low at 5512. This model exhibits higher precision and comparably lower recall.



Additionally, we examined the ROC curve, which enables us to assess the trade-offs between True Positive Rates and False Positive Rates. The ROC curve allows us to compare the TPR and FPR. The TPR was 0.52, and the FPR was 0.473. Both scores were similar, but the curve displayed a noticeable deviation from the top-left corner (0,1), indicating a gap from the ideal score of 1. When considering the slightly higher TPR, the model is more effective at correctly identifying positive cases, thereby minimizing false negatives.





The Precision-Recall curve (PR curve) reflects poor performance in terms of recall. The recall score is low at 0.53, resulting in a significant gap between the top-right corner (1,1) and the curve. Ideally, the curve should closely approach the corner, but this gap indicates a substantial distance between the corner and the curve. This reflects the model's poor recall scores, indicating that it struggles to properly distinguish positive values.

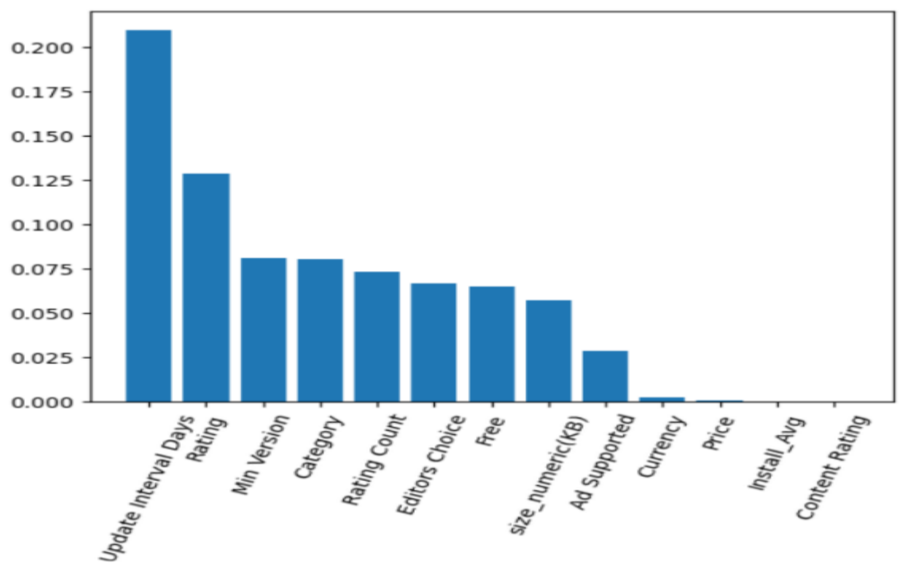
Additionally, it took 1.53 seconds to train this model.

Feature Importance

In the Random forest, the following features were considered important features in the specified order: 'Update Interval Days', 'Rating', 'Min Version', 'Category', Rating Count', 'Editors Choice', 'Free', 'size_numeric(KB)', 'Ad supported', 'Currency', 'Price', 'Installs_average' and , 'Content Rating'.

Update Interval Days' plays a significant role in reducing impurity, suggesting that it's a strong predictor for splitting the data at the root node or top-level nodes of the decision trees in the forest. 'Rating' is the second most important feature for reducing impurity, indicating its importance in making decisions in the trees. On the other hand, 'Price,' 'Installs_average,' and 'Content Rating' reduce less impurity, while the other features show similar impacts on reducing impurity.

The 'Update Interval Days' has the most significant impact. When the 'Update Interval Days' are lower (closer to 0), the average 'In App Purchases' is also lower, at around 0.16 to 0.32. As 'Update Interval Days' increase, the average 'In App Purchases' generally show an upward trend, peaking at around 0.51 for an 'Update Interval Days' of 4.9. Additionally, the 'Rating' also has a notable effect on the increase in 'In-App Purchases.' When the rating increases, the purchases have lower figures, while with an increasing rating, the purchases increase. However, when comparing other features, such as price, install_avg, and content_Rating, they did not appear to significantly affect purchase.



Decision Tree Classifier

Hyperparameter Tunning

Random search was chosen for hyperparameter tuning, as random search is a more efficient method than grid search, especially in the case of large-scale hyperparameter spaces. Accuracy was set as the scoring criterion for the random search and 5-fold cross-validation was performed. Precision measures the accuracy of the model in positive category prediction. Cross-validation helps to evaluate the performance of the model without relying too much on the randomness of a single data partition.

Best Parameters	Scoring
'min_samples_split': 6 (The minimum number of samples required to split an internal node) **'min_samples_leaf': 4** (The minimum number of samples required at a leaf node) **'max_ _depth': 7** **'criterion': gini**	**'Precision'**

Model_Tuning (Controlling imBalance)

The ratio of 1 and 0 data adjusted by the undersampling method is 1:2. Although the imbalance is not serious, we tried to further improve the model's performance by applying class weights and SMOTE.

After applying class weights and SMOTE, the F1 score improved, but the main metric we were concerned with, "precision", showed a significant decrease. Therefore, we conclude that the basic decision tree model best suits our purposes.

Basic Decision Tree	*Decision Tree_class_weight*	*Decision Tree_SMOTE*

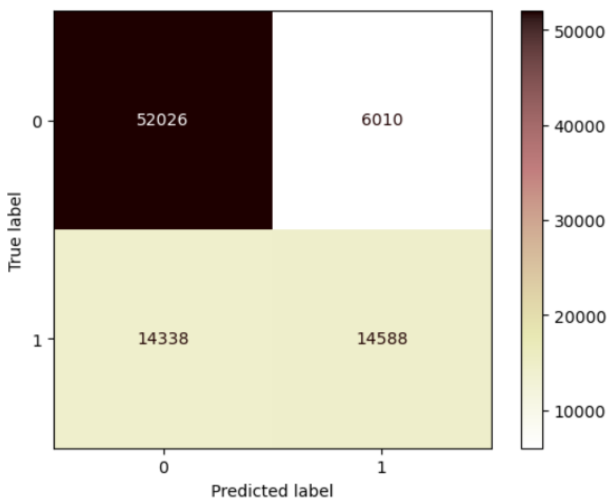
(Precision) 0.71 *(Recall) 0.50* *(F1) 0.59*	*(Precision) 0.58* *(Recall) 0.74* *(F1) 0.65*	*(Precision) 0.56* *(Recall) 0.70* *(F1) 0.62*

Model Evaluation

The test set was brought into the decision tree model with optimal hyperparameters for prediction. The resulting confusion matrix is shown below, and the model is optimized due to the imbalance in the category distribution of the target variable being balanced by the undersampling method. 0 (false) still has a higher prediction accuracy than 1 (true), but the model has a significant increase in the accuracy of the 1-category predictions.

<u>Confusion Matrix</u>

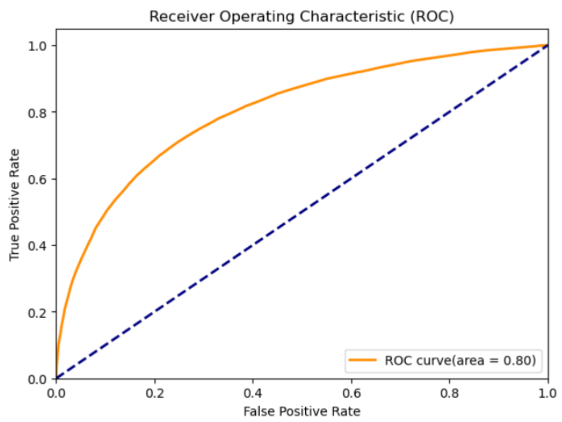
The optimal decision tree model had a precision of 0.71, a recall of 0.50, and an F1 score of 0.59. The relatively high precision and low recall indicate a large number of false negatives. The confusion matrix shows that 14,338 positive values ("purchases") were misclassified as negative values ("no purchases"). In contrast, the number of positive values misclassified in the predictions is low at 6010. The model has high precision and relatively low recall.

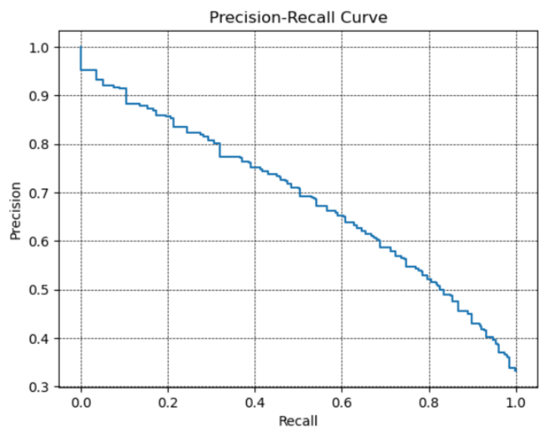


ROC Curve and Precision-Recall Curve

The ROC curve is a graphical tool used to evaluate the performance of a binary classification model, which helps me to better understand the performance of the model.AUC is a measure of the area under the ROC curve, which represents the combined performance of the model at all possible thresholds.The closer the AUC is to 1, the better the performance of the model. The model computes an AUC value of about 0.80, which is a good performance. This proves that our treatment of the imbalance problem is effective.

The Precision-Recall curve (PR curve) reflects poor recall performance. The recall score is low, resulting in a significant gap between the upper right corner (1,1) and the curve. This reflects that the model does not discriminate well on the true positive value (1).

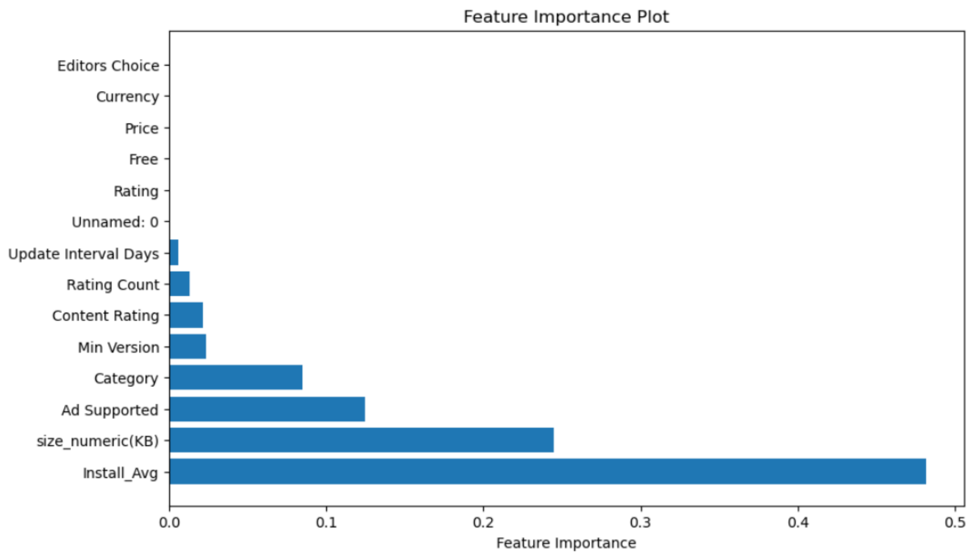




Feature Importance

Feature importance is a concept in machine learning that indicates the extent to which each feature (or variable) in a dataset contributes to the prediction or output of a model. In decision tree classification models, feature importance is usually defined by measuring the contribution of each feature during the splitting of tree nodes. This model relies on Gini impurity decrease as a measure. The greater the feature's contribution to reducing uncertainty, the higher its importance.

According to the bar chart, the following features are considered important in the specified order: "install_avg", "size_numeric(KB)", "Ad_Supported", “Category”, "Min Version", "Content Rating", "Rating Count", "Update interval Days", and “Rating”, "Free", “Price”, “Currency”, " Editors Choice" is not considered an important feature. The reason for the highest score for "install_avg" might be that this variable is equivalent to reflection of the number of people who use the app, which helps to study the presence or absence of in-app purchases.



Gradient Boosting Classifier

Hyperparameter Tunning (Cross Validation)

In hyperparameter tuning, we import the ***RandomizedSearchCV*** function from ***sklearn.model_selection*** to optimize the model's performance. We apply the best hyperparameter on the train datasets (X_train, y_train)

Best Parameters	Scoring
'n_estimators': 63 (The contribution of each tree to the final prediction) **'min_samples_split': 13** (The minimum number of samples required at a leaf node) **'min_samples_leaf': 18** (The minimum number of samples required to split an internal node) **'max_samples': 0.3** **'max_depth': 6** **'learning_rate': 0.2** **'subsample': 0.9**	**'Precision'**

Pairs of parameters were examined using cross-validation, and the best parameters were selected based on the 'Precision' score, which considers balanced model performance.

Model_Tuning (Controlling imBalance)

To enhance the data imbalance performance, we implemented class_weights and employed SMOTE (Synthetic Minority Over-sampling Technique).

Following these adjustments, the F1 score showed improvement in class_weight, although our main focus, 'precision,' didn't exhibit the same enhancement. As a result, we determined that the basic XGBoosting model, without further fine-tuning, delivered the best performance for our specific objectives.

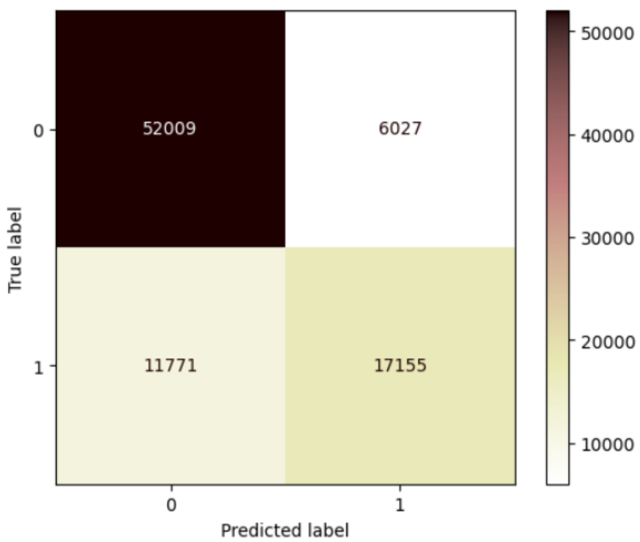
Basic XGBoosting	*XGBoosting_class_weight*	*XGBoosting_SMOTE*
(Precision) 0.74 *(Recall) 0.59* *(F1) 0.79*	*(Precision) 0.64* *(Recall) 0.76* *(F1) 0.69*	*(Precision) 0.71* *(Recall) 0.63* *(F1) 0.67*

Model Evaluation

The basic XGBoosting exhibits good precision for In-App Purchase True (0.74), indicating accurate positive predictions. However, recall In-App Purchase True for is lower (0.59), meaning some actual positives were missed. The macro-average F1-score is 0.76, and the weighted average F1-score is 0.79, indicating decent model performance across both classes.

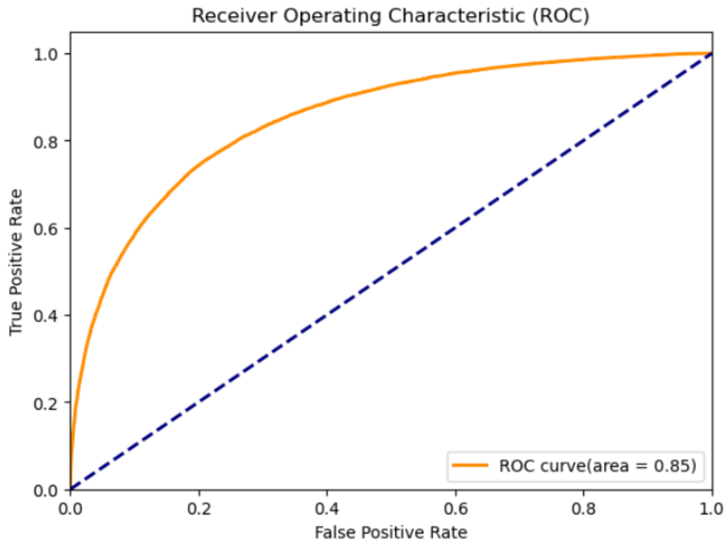
Confusion Matrix

True Negative (52,009) is extremely higher than others, indicating that the model performs better in non-in-app purchases than in-app purchases. False Negative (11,771) is greater than False Postive (6,027), suggesting that the model failed to identify as "False" when they were actually "True."



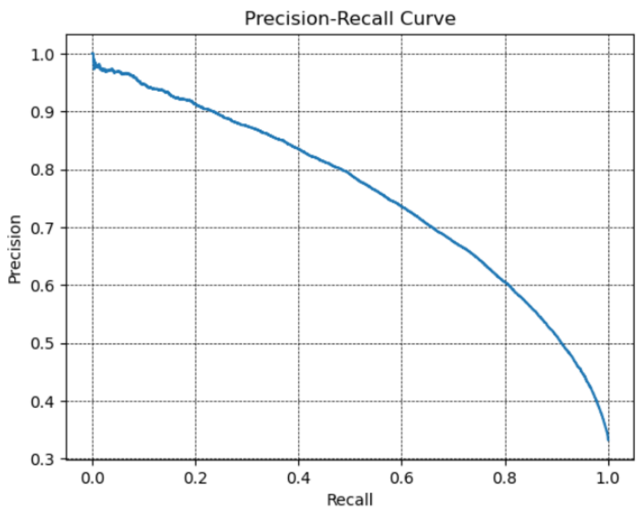
ROC Curve and AUC

The AUC value of 0.85 indicates indicates a strong model's ability to distinguish between “In-App Purchase”, with an 85% chance of correctly ranking a randomly chosen positive instance higher than a negative one.



Precision-Recall Curve

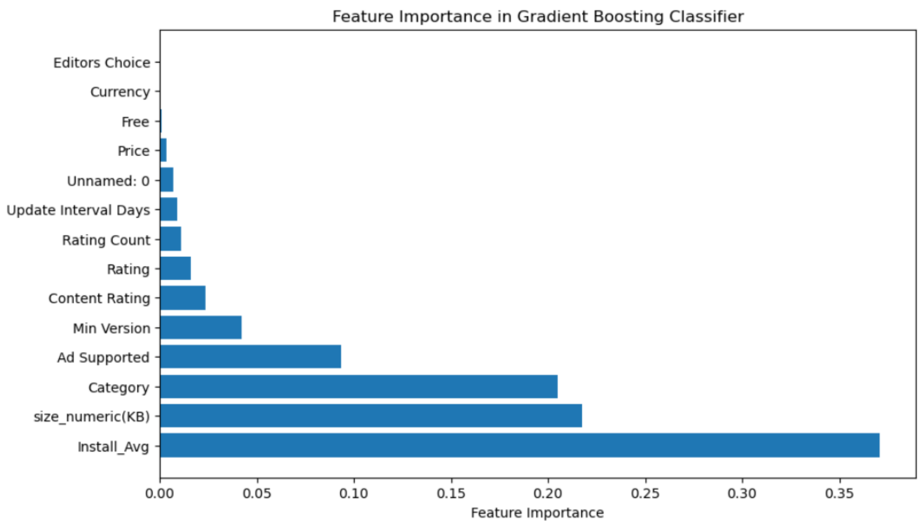
The curve showed the lower performance of recall, which only have 0.59 in the model. In an ideal scenario, we want high precision and high recall. This corresponds to a point near the top-right corner of the curve. However, the curve goes down to the right button, indicating that the model fail to classify most positive values.



Feature Importance

Feature importance provides insight into the relative importance of each feature in a model. The higher the importance, the more the feature influences the model's predictions. This information can guide us in feature selection, understanding the model's behavior, and making decisions related to model optimization and interpretability.

As you can see in the following graph, the feature importance analysis reveals that "Install_Avg" is the most crucial predictor, with an importance score of 0.371, followed by "size_numeric(KB)" and "Category". Features like "Currency," "Editors Choice" have negligible importance, which near to zero.



According to the feature importance, we notice that “Category” contain highly influence to our best model. We further analyze the proportion of each category contained “In-App Purchase” service. The result showed that 'Casio' (49%) and 'Role Playing' (46%) categories exhibited the highest proportion of in-app purchase service.

```
Category
Casino                 0.497636
Role Playing           0.467012
Strategy               0.391977
Word                   0.365006
Card                   0.332559
Simulation             0.312044
Racing                 0.292029
Dating                 0.291845
Action                 0.274832
Puzzle                 0.245427
Weather                0.241927
Board                  0.235172
Trivia                 0.207715
Adventure              0.203853
Casual                 0.194458
Arcade                 0.193282
Educational            0.183265
Parenting              0.178215
Comics                 0.167016
Music                  0.152546
Sports                 0.133016
News & Magazines       0.120821
```

Conclusion

After training the model in basic, class_weight, and SMOTE, all model perform well in basic version. We took the three basic models and compare them using “precision”, “recall”, “F1”, and time for training. The result revealed that “XGBoosting” is more performed than others.

	Precision	Recall	F1 (Ture-1 is Positive)	Time for Training
Decision Tree	0.71	0.50	0.59	1.35(sec)
Random Forest	0.73	0.53	0.61	1.53(sec)
XGBoosting	0.74	0.59	0.79	5.49(sec)

The target variable “In-App Purchase” rarely contained the information of the in-app purchases application. In other words, the variables contained class imbalance issues so we apply multiple method to fix the problem, such as “undersampling”, “class_weight”, and “SMOTE”. In the performance, we found that the model prefer “undersampling” while predicting “In-App Purchase”.

Suggestion for models

Among the best models, XGBoost demonstrated the highest precision, enabling us to propose effective strategies for boosting in-app purchases.

- **Key features that significantly influence in-app purchases:**

  'Install_avg,' 'Size_numeric(KB),' and 'Ad Supported':

  Increasing the user base, as demonstrated by 'Install_avg,' is a fundamental factor for boosting in-app purchases. Therefore, investing in advertisements to attract more users can be a successful strategy.

  'Size_numeric(KB)' may not directly influence the strategy, considering the 'Game' category's higher purchase rates suggests that larger apps may naturally result in increased purchases.

  'Category':

  We found that 'Casio' (49%) and 'Role Playing' (46%) categories exhibited the highest proportion of in-app purchase service. However, this information alone may not be sufficient to formulate a strategy for deciding whether an app should conduct in-app purchase service.

The model performs reasonably well in identifying false positives and cases with "In-App Purchase=True" but has lower recall due to prioritizing precision. The F1 score is decent, but overall accuracy falls short of the 80% target due to biased data. Using class weight and SMOTE improved model performance. While intentionally keeping the dataset imbalanced for learning purposes, better results could be achieved with more data.

Business Suggestions

In conclusion, software investors should consider investing the apps with “In-App Purchase”, as they tend to be more profitable than paying a flat fee.

"Install_avg" and "size_numeric(KB)" have a significant impact on "In-App Purchase" prediction. However, "Install_avg" data becomes available only after the launch, and "size_numeric(KB)" data can only be obtained after development is completed. Therefore, considering our investment timeline, we prioritize the "Category" feature.

All things considered, we recommend that investors consider their investment objectives in terms of "Category" in order to maximize their returns.

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