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Predicting App Usage Time

Milestone 2

DSC680-T301

Professor Iranitalab

Business Problem

Predicting app usage time for users is critical for businesses, app developers, and marketers who aim to increase app usage time and user retention by optimizing the user experience for different target demographics (Admin & Admin, 2025). Understanding the factors that influence app usage time can help businesses and developers target high-engagement users, predict app usage time, and improve customer satisfaction and user retention. App developers need insights into user behavior to provide a better user experience that fosters a personalized experience, which can help lead to longer app usage time and better user retention.

This project aims to provide actionable insights by identifying key factors associated with app usage time. Key analysis will focus on the correlation between features such as screen-on time, daily data consumption, age, gender, operating system, and device model to determine which factors are most important for predicting app usage time. Using this information, businesses can develop data-driven strategies to enhance app usage time and user retention.

Background/History

Phone usage has become ubiquitous in society, drastically changing how users interact with companies and conduct business. One important aspect of this change is evidenced by the growing trend of apps. In 2016, roughly 146 billion apps were downloaded from app stores worldwide. By 2023, this number had grown to 257 billion (Statista, 2024). It seems there is an app for everything, ranging from communication and health to education and entertainment. The pervasiveness of apps in everyday life underscores the importance of understanding user behavior, which is essential for developers and businesses looking to retain users and encourage app usage. As the app market is saturating, it is important for businesses to not only attract new users but keep the existing ones they have. This is where predictive analytics demonstrate their value to a company.

Data Explanation

The dataset used in this project is Mobile Device Usage and User Behavior Dataset found on Kaggle, uploaded by user Vala Khorasani. The dataset contains 700 samples of user data including metrics such as app usage time, screen-on time, battery drain, number of apps installed, data usage, and user specific features such as age and gender.

All features were included in the analysis and model creation steps. The data cleaning consisted of dropping 11 rows that had missing ages, scaling numerical features with a standard scaler, and using one-hot encoding on categorical features.

The target feature for the analysis is the ‘App Usage Time (MB/Day)’ feature. There were three models created for this project, a linear regression model, random forest regression model, and an XGBoost regression model.

Methods

Linear Regression Model

The linear regression model was used as a baseline for model performance. A linear regression is a statistical method used to model the relationship between a dependent variable and one or more independent variables (GeeksforGeeks, 2025).

Random Forest Regression Model

Random Forests (RF) are an ensemble learning algorithm that use a tree machine learning algorithm that builds multiple decision trees during the training phase. Each decision tree is composed of a random subset of the data set to measure a random subset of features in each partition (GeeksforGeeks, 2024). Utilizing random subsets of features introduces variability among individual trees, which can help reduce the chances of overfitting and improve overall prediction performance. The RF model aggregates the predictions of many decision trees, which provides more reliable and accurate results compared to a single decision tree.

XGBoost Model

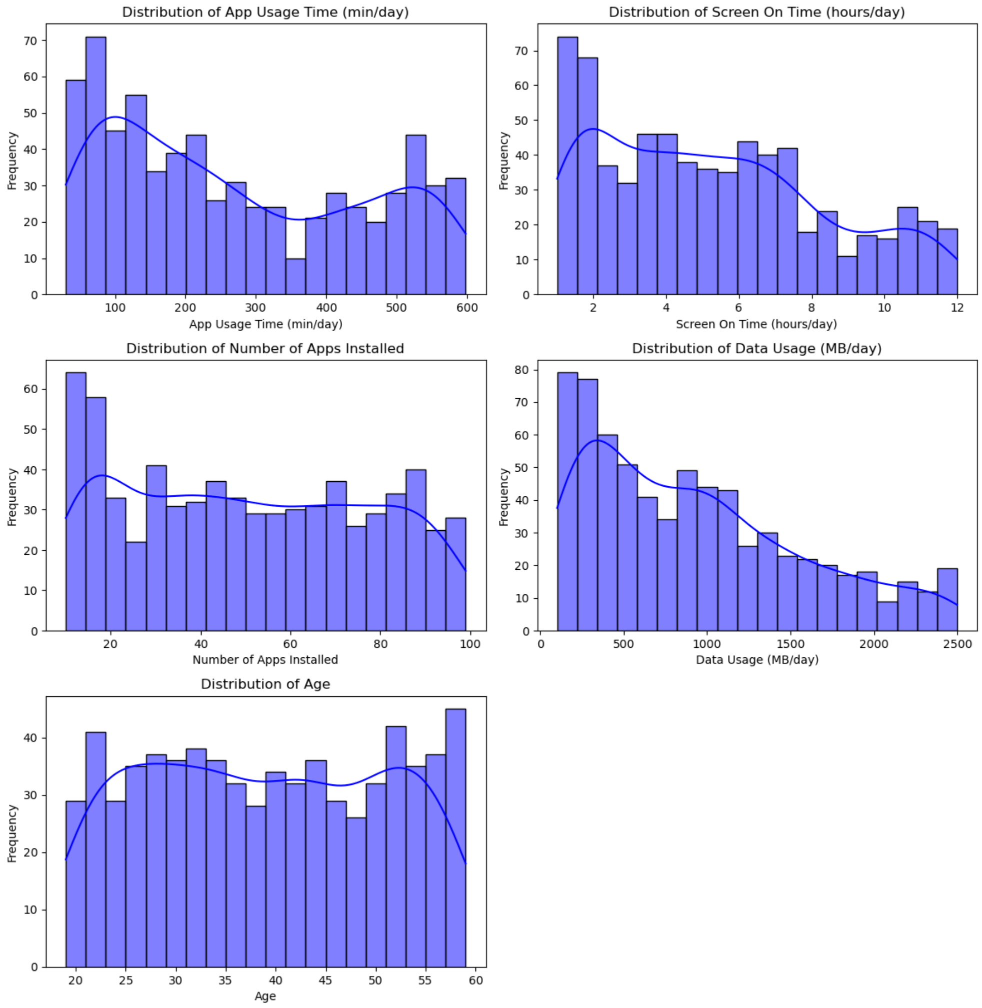
XGBoost or eXtreme Gradient Boosting is a distributed, open-source machine learning library that uses gradient boosted decision trees, a supervised learning boosting algorithm that makes use of gradient descents (Kavlakoglu & Russi, 2024).

Analysis

The goal of the analysis was to determine the answer to five different questions:

- Which age group has the highest app usage time?
- Are there any differences in app usage time between genders?
- How does daily screen time correlate with app usage time?
- Do heavier app users use significantly more data?
- Which features were the most important for model prediction?

Initial data exploration involved looking at the distribution of the numerical features:

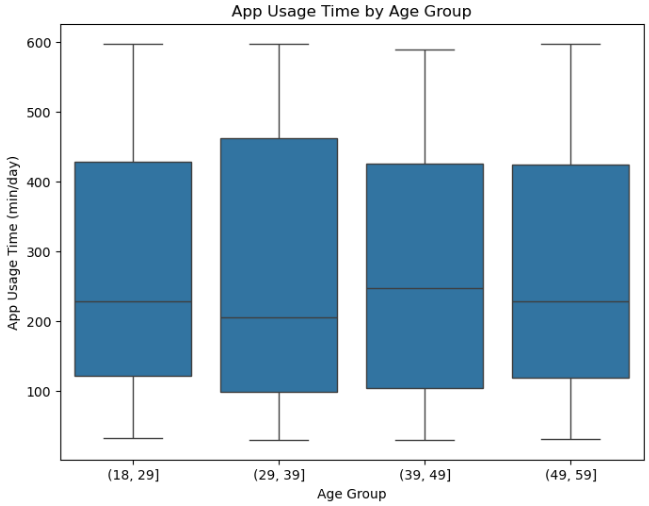


Looking at each of the different features was an important step to see if there were any clear trends in the data. The distribution of age was surprising, as it did not favor younger audiences, which is often expected in app usage studies. Rather, the distribution of age was fairly consistent across all of the age groups, which could imply that app usage is fairly widespread throughout all of the age groups.

The distributions for app usage time, screen on time, and data usage are all left skewed indicating that more users tend to use their devices less.

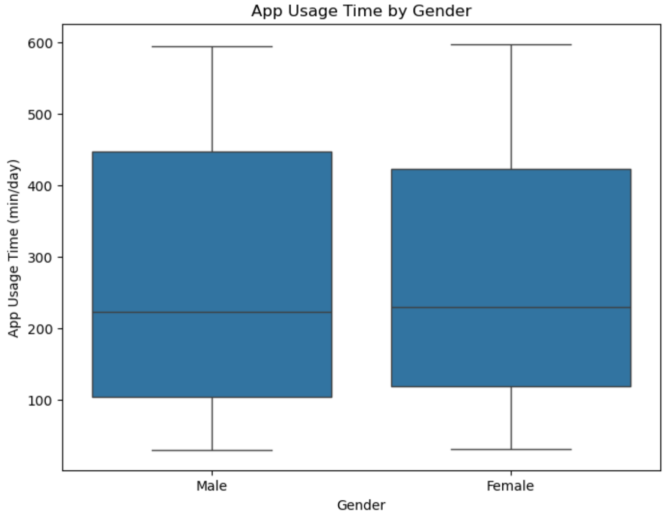
Additionally, the distribution for the number of apps installed indicated that most users have less than 20 apps installed, although the number of apps installed was consistent after the initial spike.

To answer our first question, what age group has the highest app usage time, we will look at the distribution of app usage time by age group:



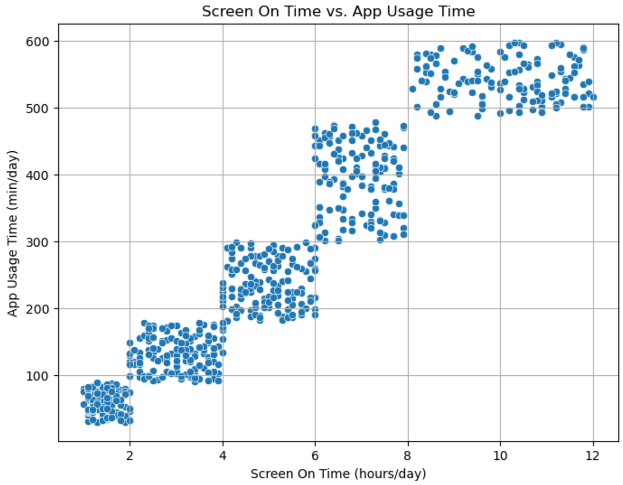
From the graph above, we can see that the 39-49 age group has a slightly higher median app usage time than the other groups. However, the groups are overall very similar.

For our second question, we will investigate whether there is any difference between the app usage time between the genders.



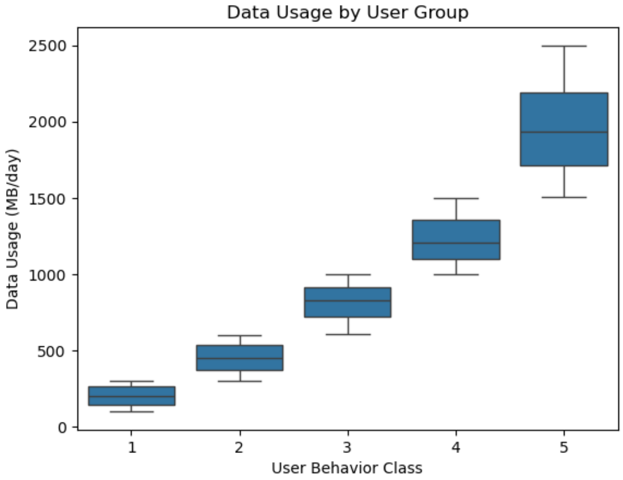
From the graph above, we can see that the app usage time between the two genders is very similar, indicating little to no difference.

Our third question was how does screen time correlate with app usage time? We will investigate this by looking at a scatterplot:



We can clearly see a positive trend in screen time vs app usage time. The longer users have their phone screen turned on, the more likely they are to be using an app.

For our fourth question, we want to see if users assigned to heavier use groups use more data than those that do not:



Again, we see that users in user behavior classes 4 and 5 tend to use more data than those in classes 1 through 3.

Now that we have answered our preliminary questions, we can move into the model building and evaluation section to determine the answer to our final question.

The goal of the analysis is to evaluate and compare the performance and applicability of the Linear Regression (LR), Random Forest (RF), and XGBoost (XBG) models. All three of the models were trained and tested on the dataset and evaluated to determine which is the best candidate for predicting app usage time.

The performance metrics used to evaluate the models were:

Root Mean Squared Error (RMSE) - is a measurement of the average difference between the model’s predicted values and its actual values (Frost, 2023).

Mean Absolute Error (MAE) - is a measurement of the absolute discrepancies between a dataset’s actual values and predicted values (GeeksforGeeks, 2024).

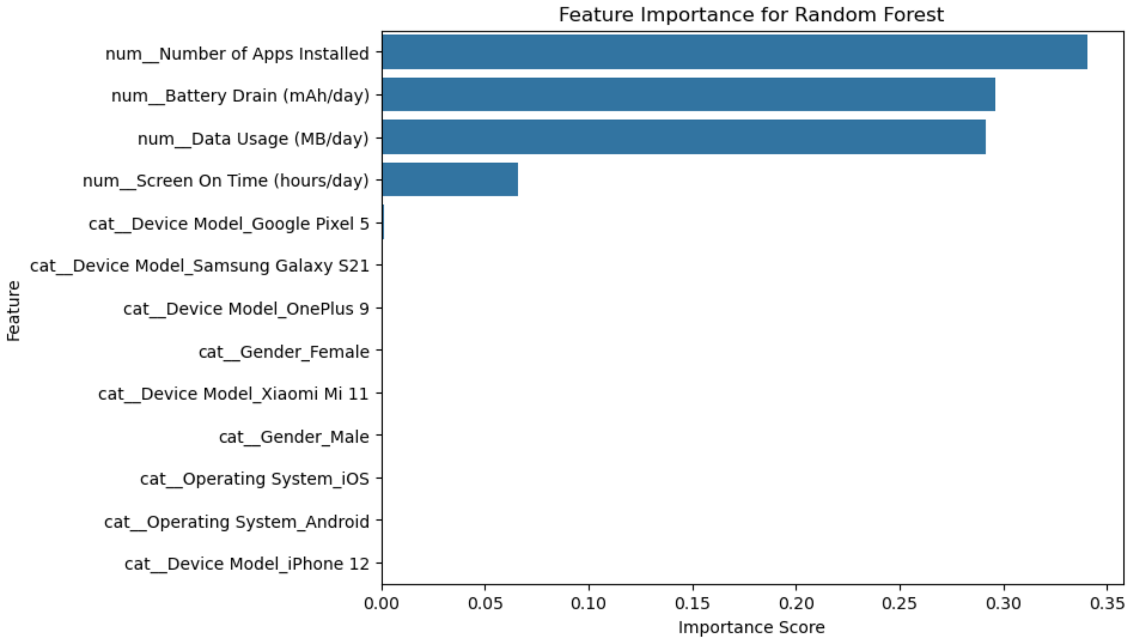
R^2 Score – is the percentage of the response variable variation that is explained by a linear model (Frost, 2017).

The models achieved these results:

Model	MAE	RMSE	R^2 Score
Linear Regression	34.745836	44.74348	93.96%
Random Forest	28.735362	35.751961	96.14%
XGBoost	31.244812	38.389111	95.56%

From these results we can see that the Random Forest model performed the best across all of the metrics.

Another key area of analysis was determining which features were the most meaningful for the model’s prediction accuracy:



From the graph above, it is clear that the most important features for predicting app usage time was the number of apps installed, daily battery drain, and daily data usage. This is unsurprising, as these factors directly relate to how often and intensively a user interacts with their phone.

Conclusion

This project aimed to investigate the features that influence app usage time and to determine which predictive model performed the best at predicting app usage time with the dataset Mobile Device Usage and User Behavior and which features were the most important for predicting app usage. Through the comparison of three models Linear Regression, Random Forest, and XGBoost, it was determined that the Random Forest Model had the best predictive performance, with the lowest MAE and RMSE scores and the highest R^2 score. The features that were most significant predictors for app usage time were number of apps installed, daily battery drain, and daily data usage. This aligns with expectations, given that these three features directly correlate with how users engage with apps on their device.

In conclusion, this project provides insight into app usage trends and the key factors influencing them. A more robust dataset could provide better information into behavioral trends. Features that would be beneficial in future analysis would include the number of notifications received daily, app types, app names, number of minutes for each app, and time between app usage.

Assumptions

There were several assumptions made in this project. First, that the dataset is accurate and representative of the population being analyzed. Second, that the dataset provided an equal representation of different user demographics, ensuring that the data is not biased in some manner. Third, that the data was collected from geographically diverse areas to avoid potential bias.

Limitations

Initially, this project was started with another dataset in mind, specifically, the Mobile Apps Screentime Analysis dataset on Kaggle. After determining that this dataset did not have any user information, it was discarded in favor of the Mobile Device Usage and User Behavior dataset. However, a combination of these two datasets would have been preferred, as both seem limited in their applicability to fully analyze how users are interacting with their phones. Future implementations of the models developed in this project would be well served to find more comprehensive datasets to analyze.

Challenges

The dataset used in this project was limited in the amount of features it had. It would have been beneficial to have more information about the specific apps being used, the duration of their use, and the number of notifications that each user received. However, this was out of scope for the dataset and efforts to find more comprehensive datasets were unsuccessful.

Future Uses/Additional Applications

Future implementations of this project are limited due to the vague nature of the dataset itself. The models used in this project are applicable to other datasets and it would be beneficial to investigate more comprehensive datasets in the future for more specific insight into predicting user behavior.

Recommendations

The dataset used in this project was limited in its number of features. It is recommended that future projects find a more comprehensive dataset.

Implementation Plan

This project was purely for academic purposes, and I would not recommend using it for business purposes.

Ethical Assessment

The ethical implications of this project were minimal. The dataset was not sensitive or personally identifiable information. Additionally, the model seemed to adequately capture the diversity of age groups and genders represented in the dataset.

References

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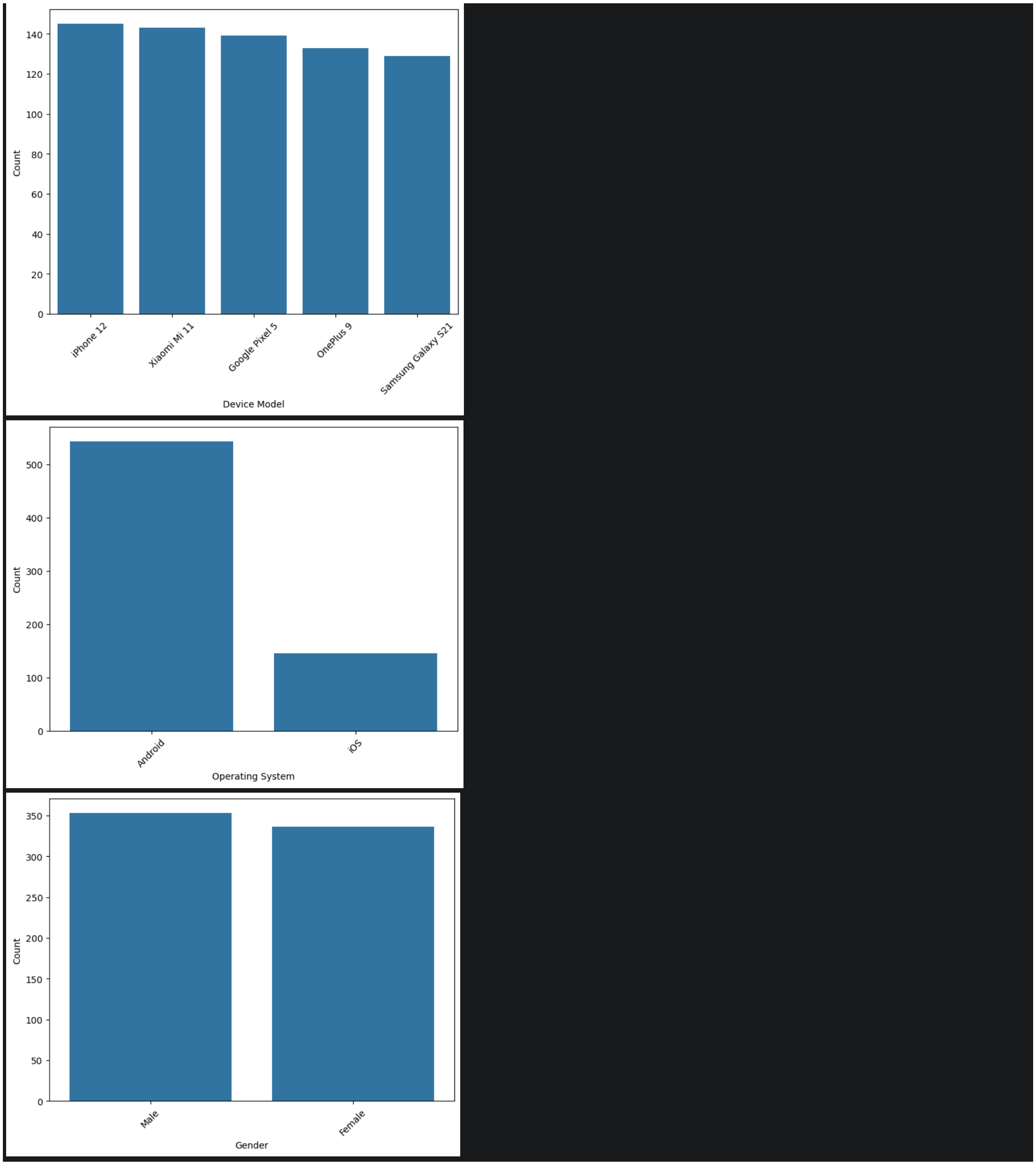
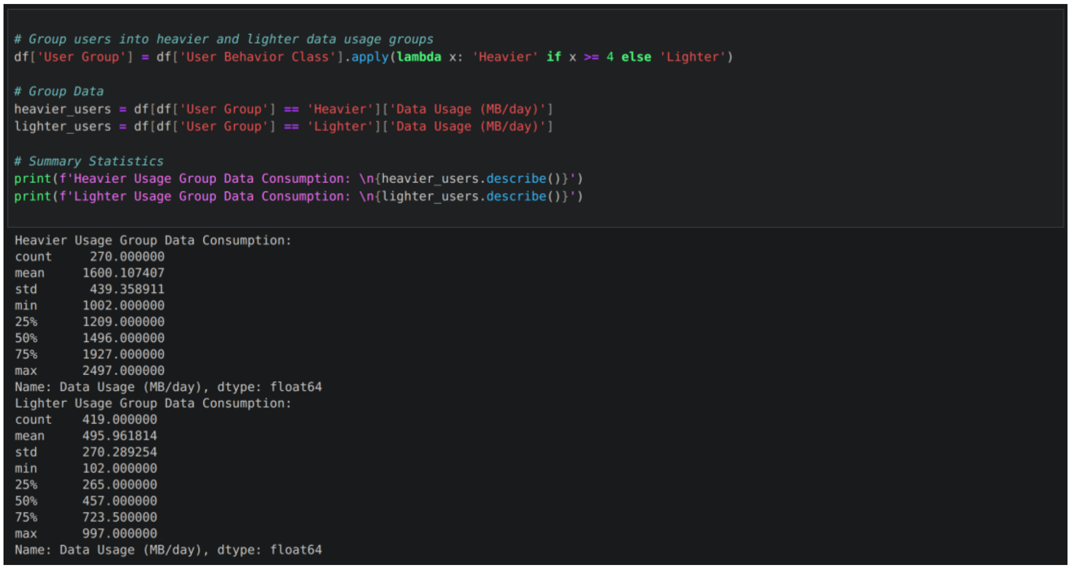
Appendix

Below are some of the EDA visualizations and code snippets that were not included in the white paper.

Bar Plots of the categorical features:



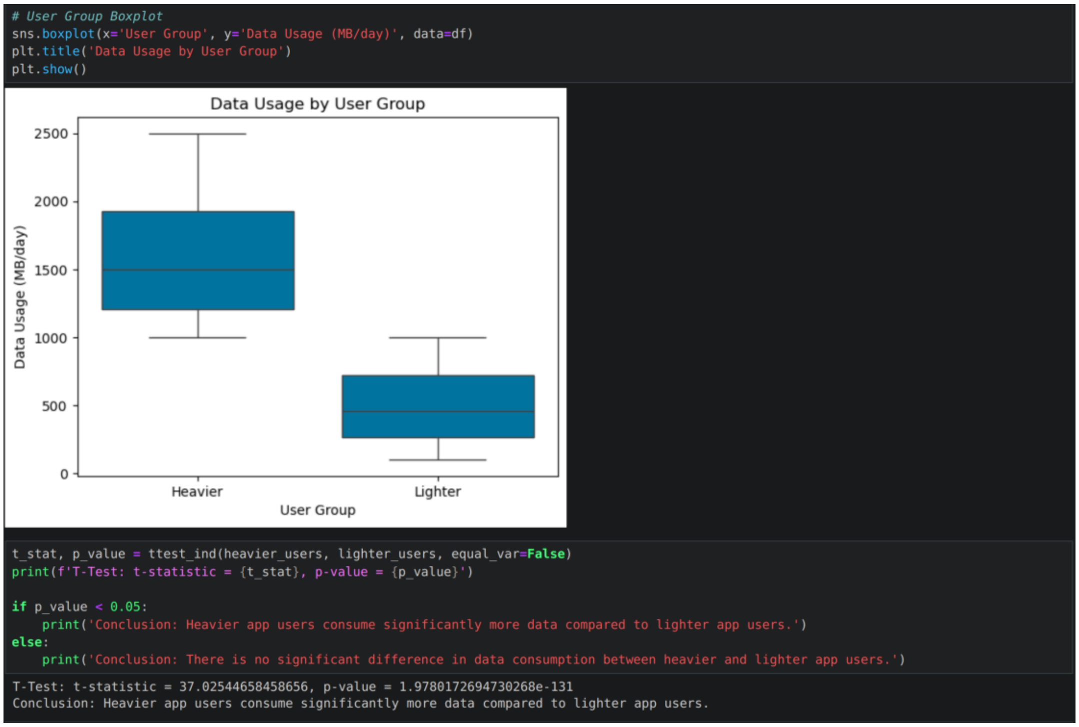
Creation of User Groups for T-Test



```
# Group users into heavier and lighter data usage groups
df['User Group'] = df['User Behavior Class'].apply(lambda x: 'Heavier' if x >= 4 else 'Lighter')

# Group Data
heavier_users = df[df['User Group'] == 'Heavier']['Data Usage (MB/day)']
lighter_users = df[df['User Group'] == 'Lighter']['Data Usage (MB/day)']

# Summary Statistics
print(f'Heavier Usage Group Data Consumption: \n{heavier_users.describe()}')
print(f'Lighter Usage Group Data Consumption: \n{lighter_users.describe()}')
```

```
Heavier Usage Group Data Consumption:
count     270.000000
mean     1600.107407
std       439.358911
min      1002.000000
25%      1209.000000
50%      1496.000000
75%      1927.000000
max      2497.000000
Name: Data Usage (MB/day), dtype: float64
Lighter Usage Group Data Consumption:
count    419.000000
mean     495.961814
std      270.289254
min      102.000000
25%      265.000000
50%      457.000000
75%      723.500000
max      997.000000
Name: Data Usage (MB/day), dtype: float64
```

T-Test for statistical significance in data usage between data usage groups.

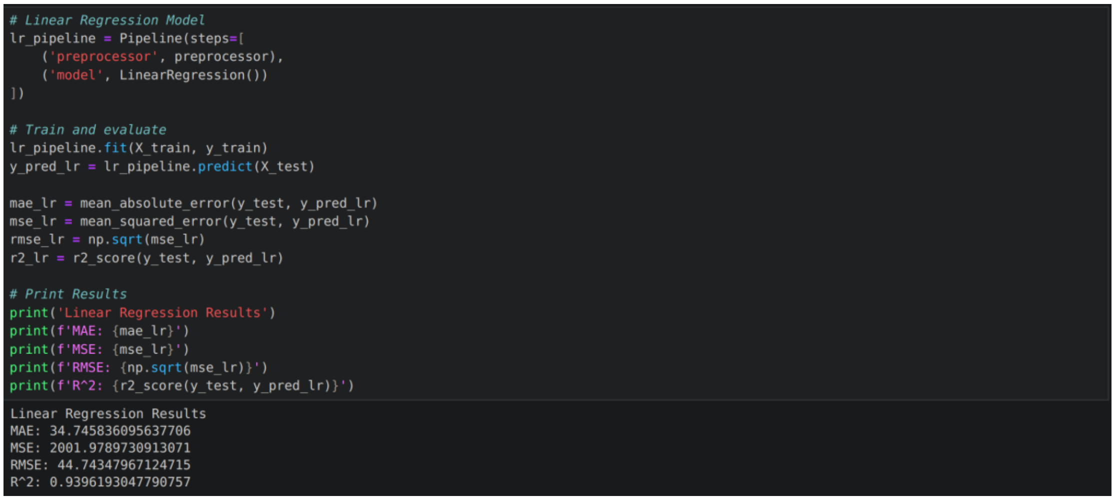


```
# User Group Boxplot
sns.boxplot(x='User Group', y='Data Usage (MB/day)', data=df)
plt.title('Data Usage by User Group')
plt.show()
```

```
t_stat, p_value = ttest_ind(heavier_users, lighter_users, equal_var=False)
print(f'T-Test: t-statistic = {t_stat}, p-value = {p_value}')

if p_value < 0.05:
    print('Conclusion: Heavier app users consume significantly more data compared to lighter app users.')
else:
    print('Conclusion: There is no significant difference in data consumption between heavier and lighter app users.')
```

```
T-Test: t-statistic = 37.02544658458656, p-value = 1.9780172694730268e-131
Conclusion: Heavier app users consume significantly more data compared to lighter app users.
```

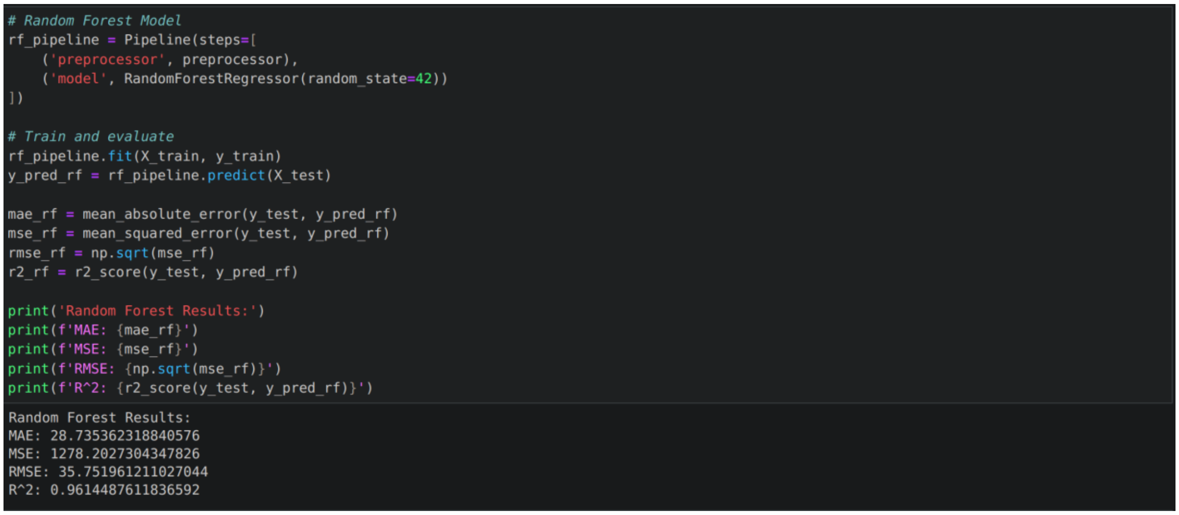
Linear Regression Model Creation



```
# Linear Regression Model
lr_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('model', LinearRegression())
])

# Train and evaluate
lr_pipeline.fit(X_train, y_train)
y_pred_lr = lr_pipeline.predict(X_test)

mae_lr = mean_absolute_error(y_test, y_pred_lr)
mse_lr = mean_squared_error(y_test, y_pred_lr)
rmse_lr = np.sqrt(mse_lr)
r2_lr = r2_score(y_test, y_pred_lr)

# Print Results
print('Linear Regression Results')
print(f'MAE: {mae_lr}')
print(f'MSE: {mse_lr}')
print(f'RMSE: {np.sqrt(mse_lr)}')
print(f'R^2: {r2_score(y_test, y_pred_lr)}')
```

```
Linear Regression Results
MAE: 34.745836095637706
MSE: 2001.9789730913071
RMSE: 44.74347967124715
R^2: 0.9396193047790757
```

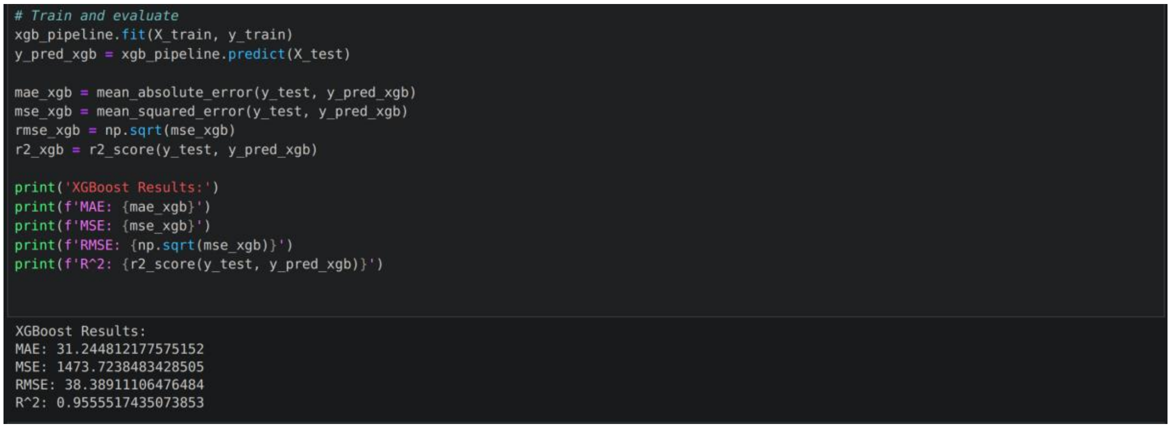
Random Forest Model Creation



```
# Random Forest Model
rf_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('model', RandomForestRegressor(random_state=42))
])

# Train and evaluate
rf_pipeline.fit(X_train, y_train)
y_pred_rf = rf_pipeline.predict(X_test)

mae_rf = mean_absolute_error(y_test, y_pred_rf)
mse_rf = mean_squared_error(y_test, y_pred_rf)
rmse_rf = np.sqrt(mse_rf)
r2_rf = r2_score(y_test, y_pred_rf)

print('Random Forest Results:')
print(f'MAE: {mae_rf}')
print(f'MSE: {mse_rf}')
print(f'RMSE: {np.sqrt(mse_rf)}')
print(f'R^2: {r2_score(y_test, y_pred_rf)}')
```

```
Random Forest Results:
MAE: 28.735362318840576
MSE: 1278.2027304347826
RMSE: 35.751961211027044
R^2: 0.9614487611836592
```

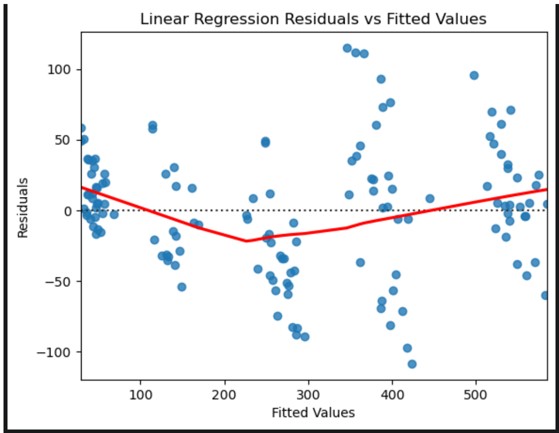
XGBoost Model Creation

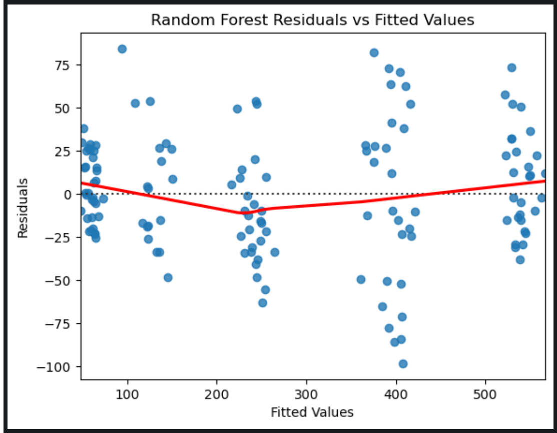


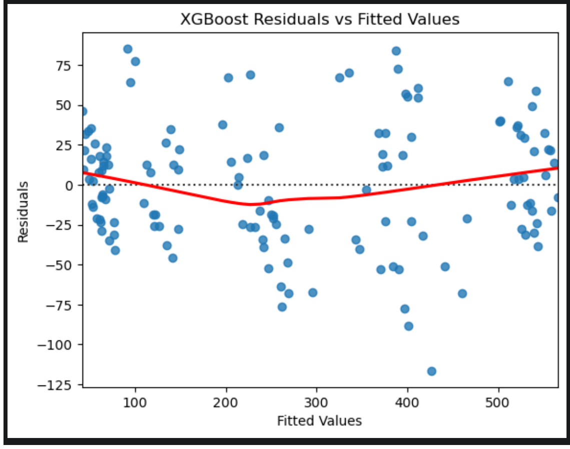
```
# Train and evaluate
xgb_pipeline.fit(X_train, y_train)
y_pred_xgb = xgb_pipeline.predict(X_test)

mae_xgb = mean_absolute_error(y_test, y_pred_xgb)
mse_xgb = mean_squared_error(y_test, y_pred_xgb)
rmse_xgb = np.sqrt(mse_xgb)
r2_xgb = r2_score(y_test, y_pred_xgb)

print('XGBoost Results:')
print(f'MAE: {mae_xgb}')
print(f'MSE: {mse_xgb}')
print(f'RMSE: {np.sqrt(mse_xgb)}')
print(f'R^2: {r2_score(y_test, y_pred_xgb)}')
```

```
XGBoost Results:
MAE: 31.244812177575152
MSE: 1473.7238483428505
RMSE: 38.38911106476484
R^2: 0.9555517435073853
```

Residual Plots for the models:


Linear Regression Residuals vs Fitted Values
Residuals
100
50
0
−50
−100
Fitted Values
100
200
300
400
500


Random Forest Residuals vs Fitted Values
Residuals
75
50
25
0
−25
−50
−75
−100
Fitted Values
100
200
300
400
500


XGBoost Residuals vs Fitted Values
Residuals
75
50
25
0
−25
−50
−75
−100
−125
Fitted Values
100
200
300
400
500

Ten Questions an audience would ask:

1. Why did you choose the Mobile Device Usage and User Behavior dataset?
2. How did you handle any incomplete or missing data?
3. What made the Random Forest model outperform the Linear Regression and XGBoost models?
4. Were there any features that surprised you by being less significant predictors of app usage?
5. Did you find any unexpected trends or patterns in the data?
6. Do you think that the data might have potential bias?
7. What specific industries or organizations could benefit from the models developed in this project?
8. If you had a more comprehensive dataset, which new research questions would you want to explore?
9. Could your predictive model be integrated into mobile app development to optimize user engagement?
10. What was the average app usage time?