Dropout Risk Prediction Report

Author: Zaynap Ahmad **Date:** August 3, 2025 **Track:** Machine Learning **Task:** Train a model that predicts dropout risk based on session frequency, time spent, and progress logs. Visualize results and provide key takeaways.

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1. **Dataset Selection and Justification**

I used the dataset provided in the data analysis task as the foundation for this modeling exercise.

Why this dataset was used:

- It already contains rich behavioral and demographic indicators.
- It includes the dropout label.
- It's session-level, allowing us to engineer user-level behavioral trends.

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2. **Feature Engineering**

Since the task was to predict dropout based on **session frequency**, **time spent**, and **progress logs**, I engineered the following features per user:

- **Session Frequency:** Average number of sessions per day since signup.
- **Time Spent:** Average session duration in minutes.
- **Progress Logs:** Check-in rate (percentage of sessions where goals were marked as completed).

These features were aggregated on a per-user basis using `.groupby('user_id')`, so the prediction is at the **user level**, not session level.

	session_frequency	time_spent	progress_logs	dropoff_flag
user_id				
U0001	0.417873	48.819440	0.473447	0.0
U0002	0.249025	59.189524	0.421071	0.0
U0003	0.409401	50.924380	0.454793	0.0
U0004	0.447314	58.647516	0.727753	1.0
U0005	0.381286	58.973333	0.296667	0.0
...	...	...	...	...
U0996	0.208427	49.217687	0.356463	0.0
U0997	0.265032	47.709293	0.487916	0.0
U0998	0.335638	49.682104	0.676317	0.0
U0999	0.368402	55.974675	0.785777	0.0
U1000	0.324251	44.873333	0.910000	1.0

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3. **Target Imbalance Analysis**

Dropout (`dropoff_flag`) was highly imbalanced:

- **Dropouts (1):** ~6%
- **Non-dropouts (0):** ~94%

This would bias the model toward always predicting "stay". To handle that, I applied **SMOTE (Synthetic Minority Over-sampling Technique)** during training and cross-validation.

This also indicated that recall is a more appropriate evaluation metric than accuracy, since our main concern is correctly identifying users who are likely to drop out, rather than just maximizing overall accuracy.

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4. **Model Selection Process**

Tried Models:

- **Logistic Regression**: Performed poorly on dropout recall.
- **Random Forest**: Stronger overall but still low recall.
- **XGBoost** : recall was lower than Gradient Boosting.
- **Gradient Boosting (Chosen)**: Best recall after SMOTE & tuning.

Why Gradient Boosting:

- Performs well on tabular data.
- Can handle small datasets effectively.
- Works well with class imbalance and is robust to outliers.

Cross-Validation:

- Used **StratifiedKFold (n=5)** to maintain class proportions in each fold.
- Scoring metric: **Recall** (focus on catching actual dropouts).

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5. **Final Model Performance**

🔹 Classification Report (Test Set):

```
              precision    recall  f1-score   support

         0.0      0.917     0.711     0.801       266
         1.0      0.181     0.500     0.266        34

    accuracy                          0.687       300
   macro avg      0.549     0.605     0.533       300
weighted avg      0.834     0.687     0.740       300
```

🔹 Cross-Validation Recall Scores (Dropout Class):

```
[0.318, 0.478, 0.478, 0.304, 0.521]
Average Recall: **0.42**
```

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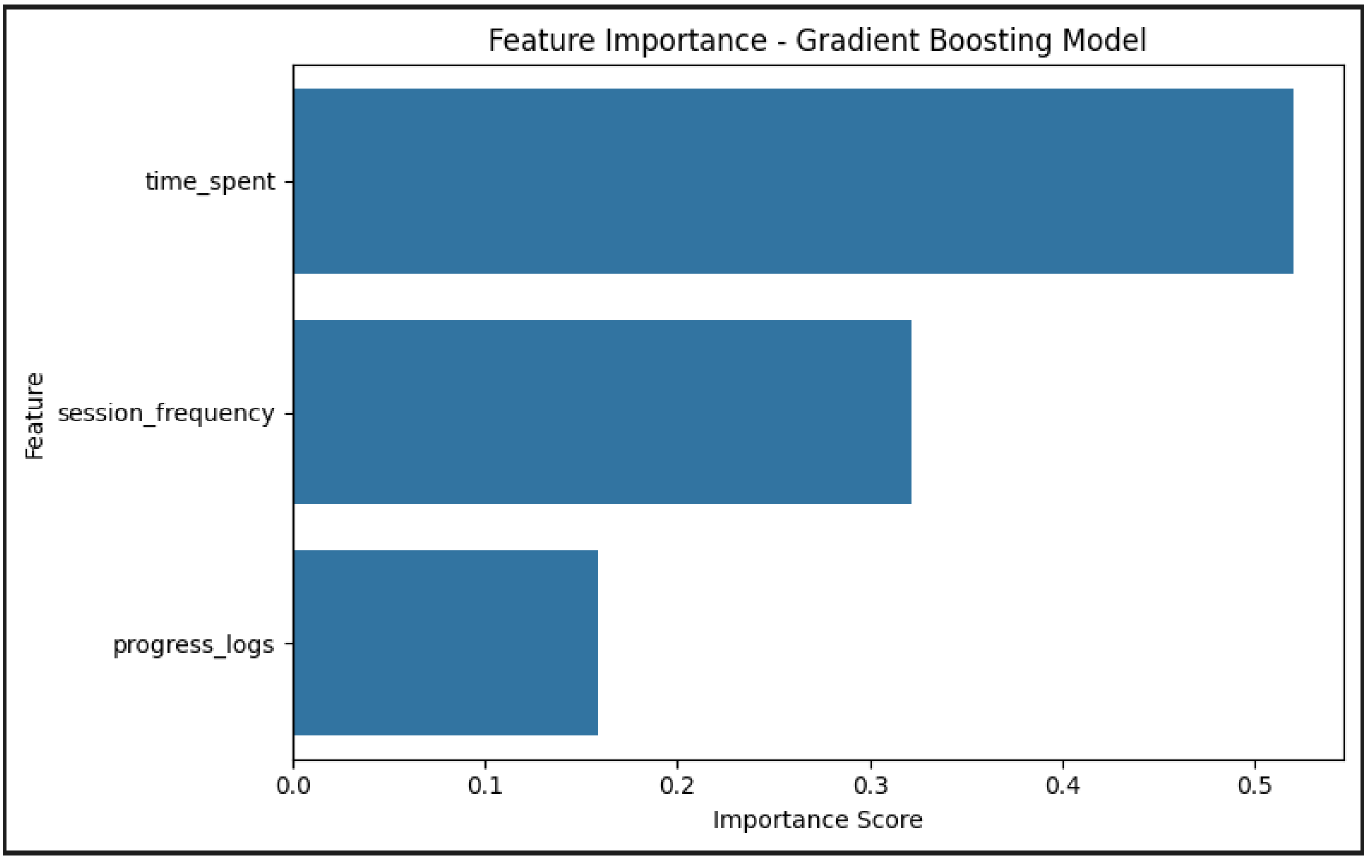
6. **Feature Importance**

> Session frequency was the most important indicator of dropout behavior.



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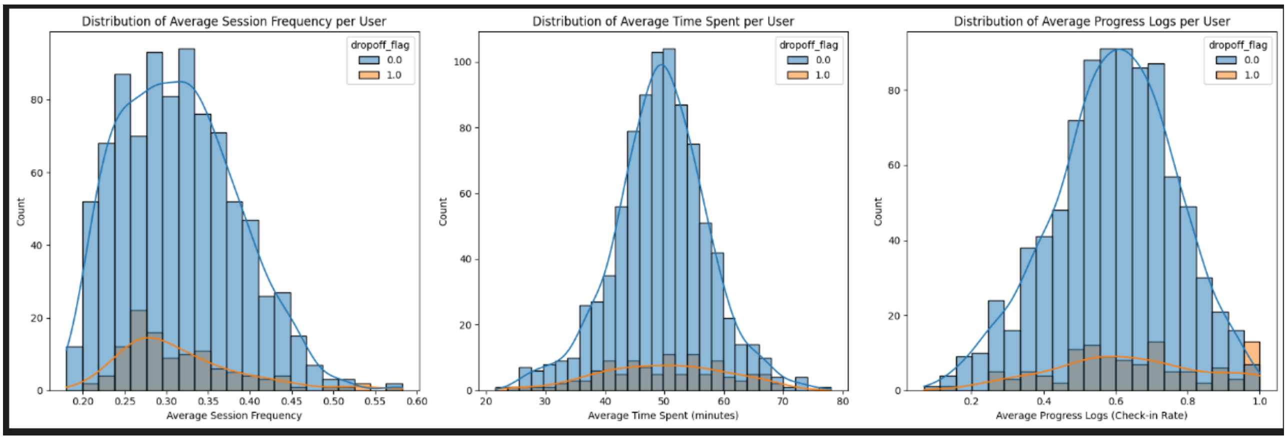
7. **Key Takeaways**

Insights:

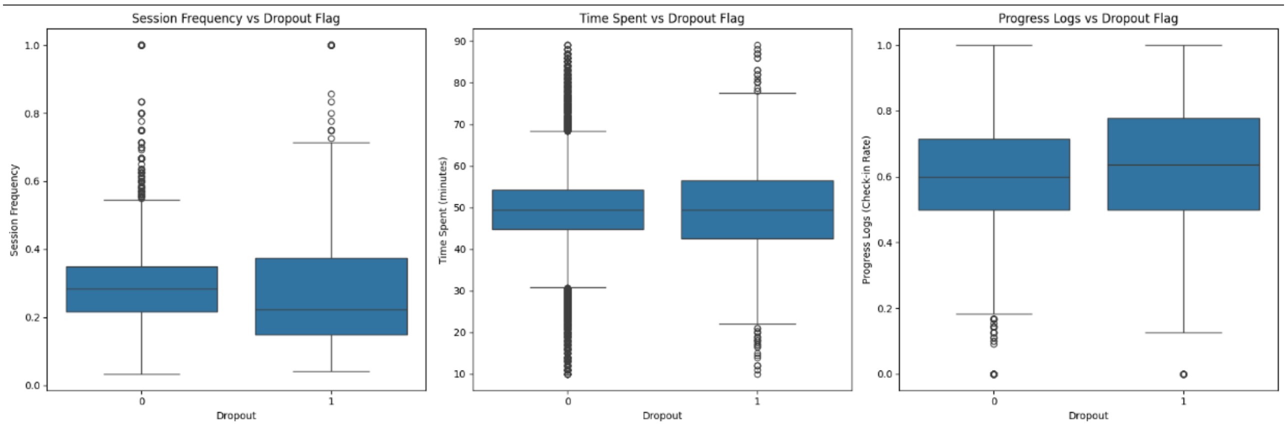
- Users with **low session frequency** and **low check-in rates** are much more likely to drop out.
- Dropout prediction is a **class imbalance problem**, so we focused on **recall**.
- Gradient Boosting + SMOTE gave the best trade-off between recall and general performance.

Visualizations:

- Distribution plots of session frequency, time spent, and progress logs by dropout flag.



- Boxplots comparing features across dropouts vs non-dropouts.



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9. **Deliverables**

File	Description
`main.ipynb`	Full EDA, feature engineering, training logic, validation, and evaluation.
`dropout_gb_model.pkl`	Trained Gradient Boosting model.
`predict_dropout.py`	Prediction script with user input.
`dropout_risk_report.md`	This report.

Additional Notes:

For full experimentation history, parameter trials, and alternative models, please refer to the notebook: **X_clan_ML_draft.ipynb** in the draft folder

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