Retain the Legends:

Predicting & Preventing Churn - Apex Legends S15

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Behind the Eclipse: What Drives This Study

Inspiration

My gamer & game-art roots sparked a deep dive into why Season 15 Eclipse players drop off.

Scope

Season 15 ‘Eclipse’ isolates a single meta, avoiding cross-patch noise.

Objective

a 7-day churn early-warning system for design, live-ops, and monetization.

The Churn Challenge

- **Churn rate:** ~70.9 % of player match observations go silent (≥ 7 days idle)
- **Key question:** Can match‑level stats, legend choices, and play‑cadence forecast churn one week ahead?
- **Process:** Data wrangling, exploratory analysis & insight generation, feature engineering, model training/evaluation & interpretation via feature importances.

Eclipse Allies: Stakeholder Lineup

Game Design (Respawn leads):
Use churn insights to rotate legends and tweak balance.

Live-Ops (Product managers):
Trigger events/reminders before 7-day inactivity, when predicted risk crosses threshold.

Marketing (Strategists):
Send targeted outreach when play frequency declines.

Monetization (Teams):
Time battle pass & bundles around churn-risk peaks.

Pipeline Game Plan

- **Dataset:** Apex Legends Season 15 (Ranked) · target 7-day churn
- **Workflow:** Prep → split → compare models → tune → test → set decision threshold
- **Models: L**ogistic Regression, Random Forest, XGBoost
- **Tools:** Python (pandas, NumPy, scikit-learn, imbalanced-learn/SMOTE), matplotlib, seaborn · Jupyter

Data Lens:

https://www.kaggle.com/datasets/d8tary/apex-legends-season-15-ranked-dataset-raw

Key Features (36 columns incl. 2 empty → 34 usable; Nov 3, 2022–Jan 15, 2023):

- **Combat:** my_kills, my_damage, my_assists
- **Legends & Squads:** my_legend, legend_diversity (engineered), teammate_count (proxy for squad size)
- **Cadence:** session_frequency (7-day, engineered), days_since_last_match (engineered)
- **Performance:** squad_placed, my_revives, my_knocks

0	date	499 non-null	datetime64[ns]
1	game	499 non-null	int64
2	map	499 non-null	object
3	match_type	499 non-null	object
4	my_duration	265 non-null	float64
5	my_rank	498 non-null	object
6	rp_earned	487 non-null	float64
7	premade_squad	497 non-null	object
8	voice_chat	497 non-null	object
9	squad_placed	475 non-null	float64
10	teamate_count	314 non-null	float64
11	my_quit	317 non-null	float64
12	teamate_quit_count	306 non-null	float64
13	my_legend	287 non-null	object
14	teamate_1_legend	277 non-null	object
15	teamate_2_legend	269 non-null	object
16	my_damage	284 non-null	float64
17	teamate_1_damage	275 non-null	float64
18	teamate_2_damage	270 non-null	float64
19	my_kills	283 non-null	float64
20	teamate_1_kills	278 non-null	float64
21	teamate_2_kills	274 non-null	float64
22	my_assists	281 non-null	float64
23	teamate_1_assists	277 non-null	float64
24	teamate_2_assists	273 non-null	float64
25	my_knocks	281 non-null	float64
26	teamate_1_knocks	278 non-null	float64
27	teamate_2_knocks	273 non-null	float64
28	my_revives	283 non-null	float64
29	teamate_1_revives	277 non-null	float64
30	teamate_2_revives	274 non-null	float64
31	my_respawns	283 non-null	float64
32	teamate_1_respawns	276 non-null	float64
33	teamate_2_respawns	275 non-null	float64
34	Unnamed: 34	0 non-null	float64
35	Unnamed: 35	0 non-null	float64

Data Recon: Initial Inspection

- **df.head():**
- **df.shape:** (499, 36)
- **df.describe()**
- **df.columns**
- **df.isna().sum()**
- **df.duplicated().sum()**

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 499 entries, 0 to 498
Data columns (total 36 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   date                499 non-null    datetime64[ns]
 1   game                499 non-null    int64
 2   map                 499 non-null    object
 3   match_type          499 non-null    object
 4   my_duration         265 non-null    float64
 5   my_rank             498 non-null    object
 6   rp_earned           487 non-null    float64
 7   premade_squad       497 non-null    object
 8   voice_chat          497 non-null    object
 9   squad_placed        475 non-null    float64
 10  teamate_count       314 non-null    float64
 11  my_quit             317 non-null    float64
 12  teamate_quit_count  306 non-null    float64
 13  my_legend           287 non-null    object
 14  teamate_1_legend    277 non-null    object
 15  teamate_2_legend    269 non-null    object
 16  my_damage           284 non-null    float64
 17  teamate_1_damage    275 non-null    float64
 18  teamate_2_damage    270 non-null    float64
 19  my_kills            283 non-null    float64
 20  teamate_1_kills     278 non-null    float64
 21  teamate_2_kills     274 non-null    float64
 22  my_assists          281 non-null    float64
 23  teamate_1_assists   277 non-null    float64
 24  teamate_2_assists   273 non-null    float64
 25  my_knocks           281 non-null    float64
 26  teamate_1_knocks    278 non-null    float64
 27  teamate_2_knocks    273 non-null    float64
 28  my_revives          283 non-null    float64
 29  teamate_1_revives   277 non-null    float64
 30  teamate_2_revives   274 non-null    float64
 31  my_respawns         283 non-null    float64
 32  teamate_1_respawns  276 non-null    float64
 33  teamate_2_respawns  275 non-null    float64
 34  Unnamed: 34         0 non-null      float64
 35  Unnamed: 35         0 non-null      float64
dtypes: datetime64[ns](1), float64(26), int64(1), object(8)
memory usage: 140.5+ KB
```

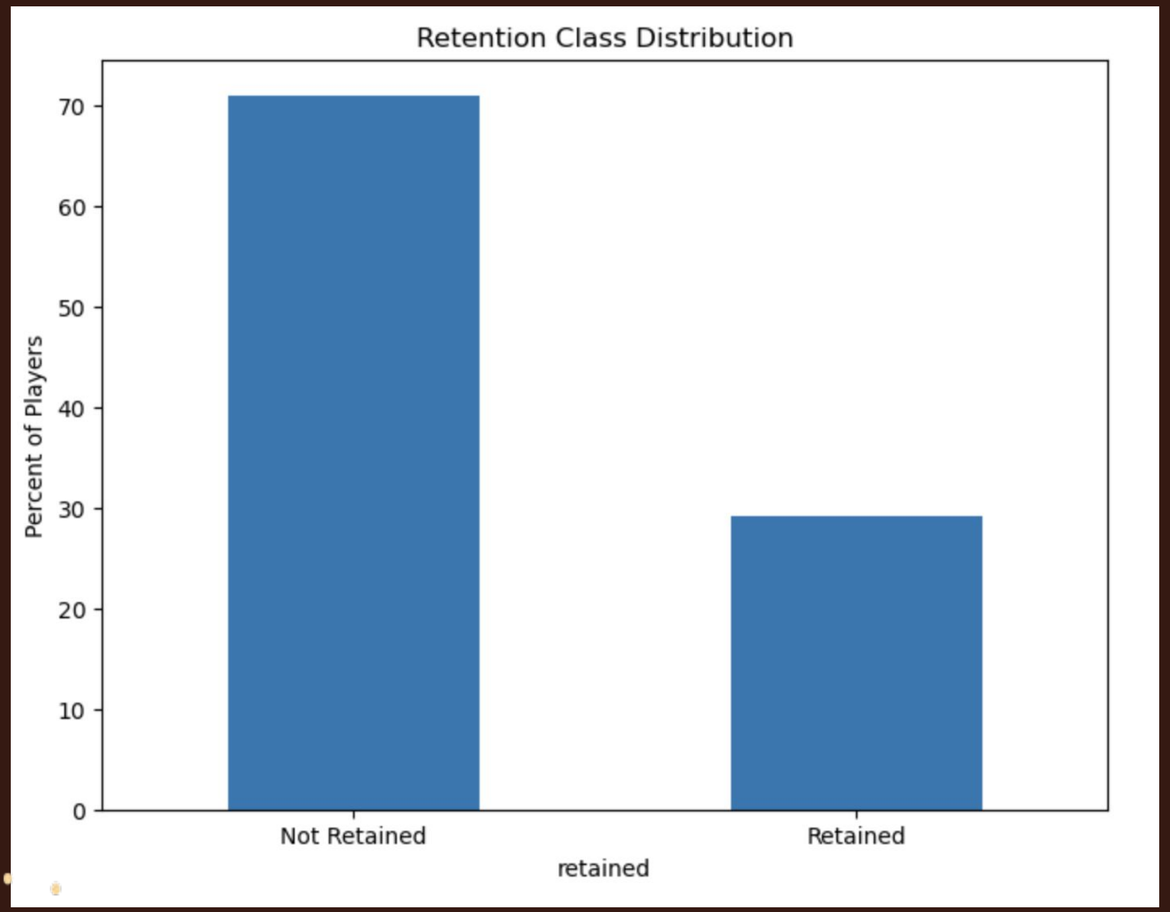
```
df.dtypes
```

```
date                  datetime64[ns]
game                           int64
map                           object
match_type                    object
my_duration                  float64
my_rank                       object
premade_squad                 object
voice_chat                    object
squad_placed                 float64
teamate_count                float64
teamate_quit_count           float64
my_legend                     object
teamate_1_legend              object
teamate_2_legend              object
my_damage                    float64
teamate_1_damage             float64
teamate_2_damage             float64
my_kills                       int64
teamate_1_kills                int64
teamate_2_kills                int64
my_assists                     int64
teamate_1_assists              int64
teamate_2_assists              int64
my_knocks                      int64
teamate_1_knocks               int64
teamate_2_knocks               int64
my_revives                     int64
teamate_1_revives              int64
teamate_2_revives              int64
my_respawns                    int64
teamate_1_respawns             int64
teamate_2_respawns             int64
dtype: object
```

Forge the Data - Data Cleaning

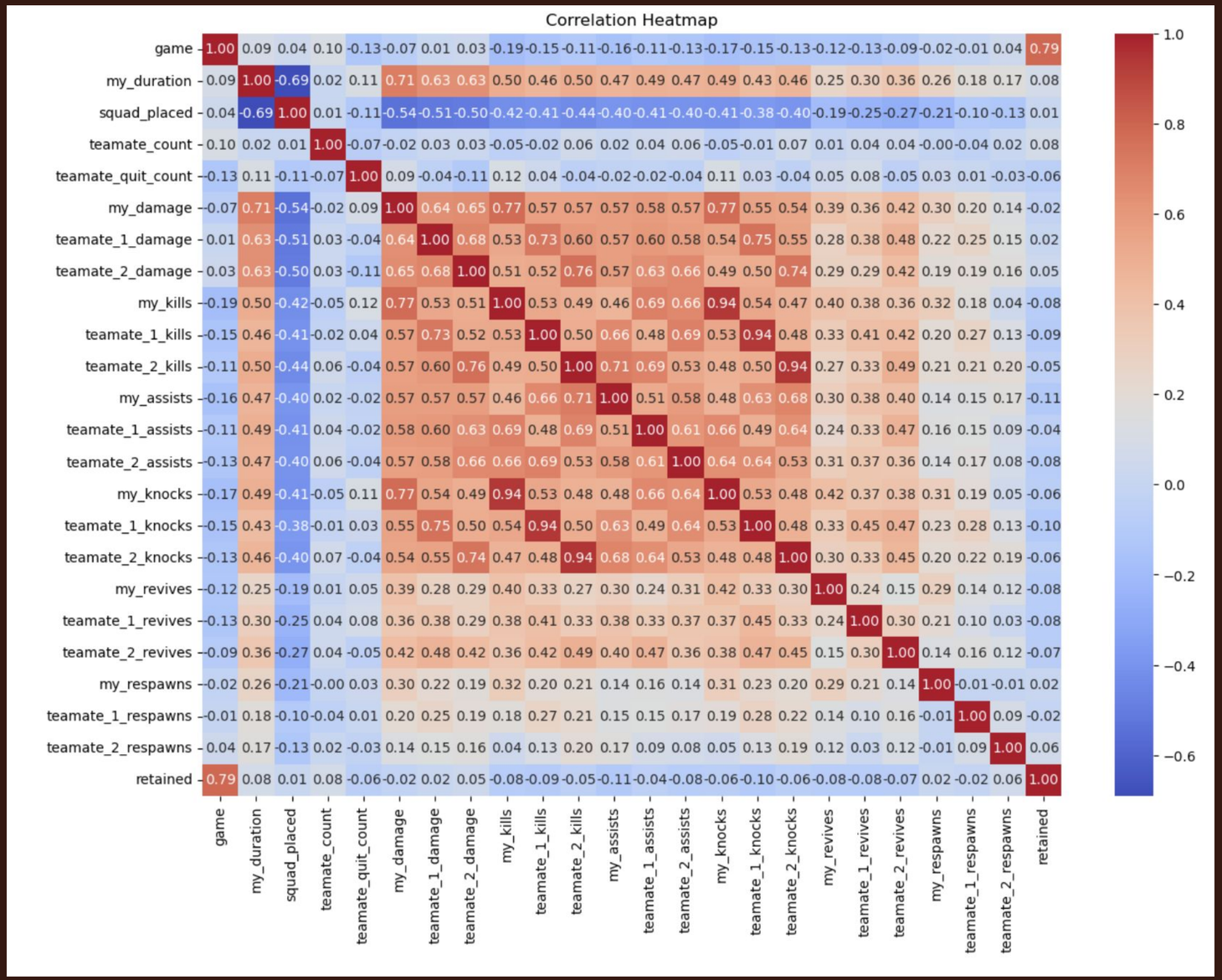
- **Duplicates:** df.duplicated().sum() → none
- **Drop columns:** Unnamed:34, Unnamed:35 *(placeholders)*; RP/quit/Ids, any all-NaN
- **Missing values:** counts (*my_ / teammate_*) → fill NA - 0, then cast to int; other numeric → median; categorical → mode
- **Final shape:** 499 rows × 32 columns

Churn Distribution : EDA



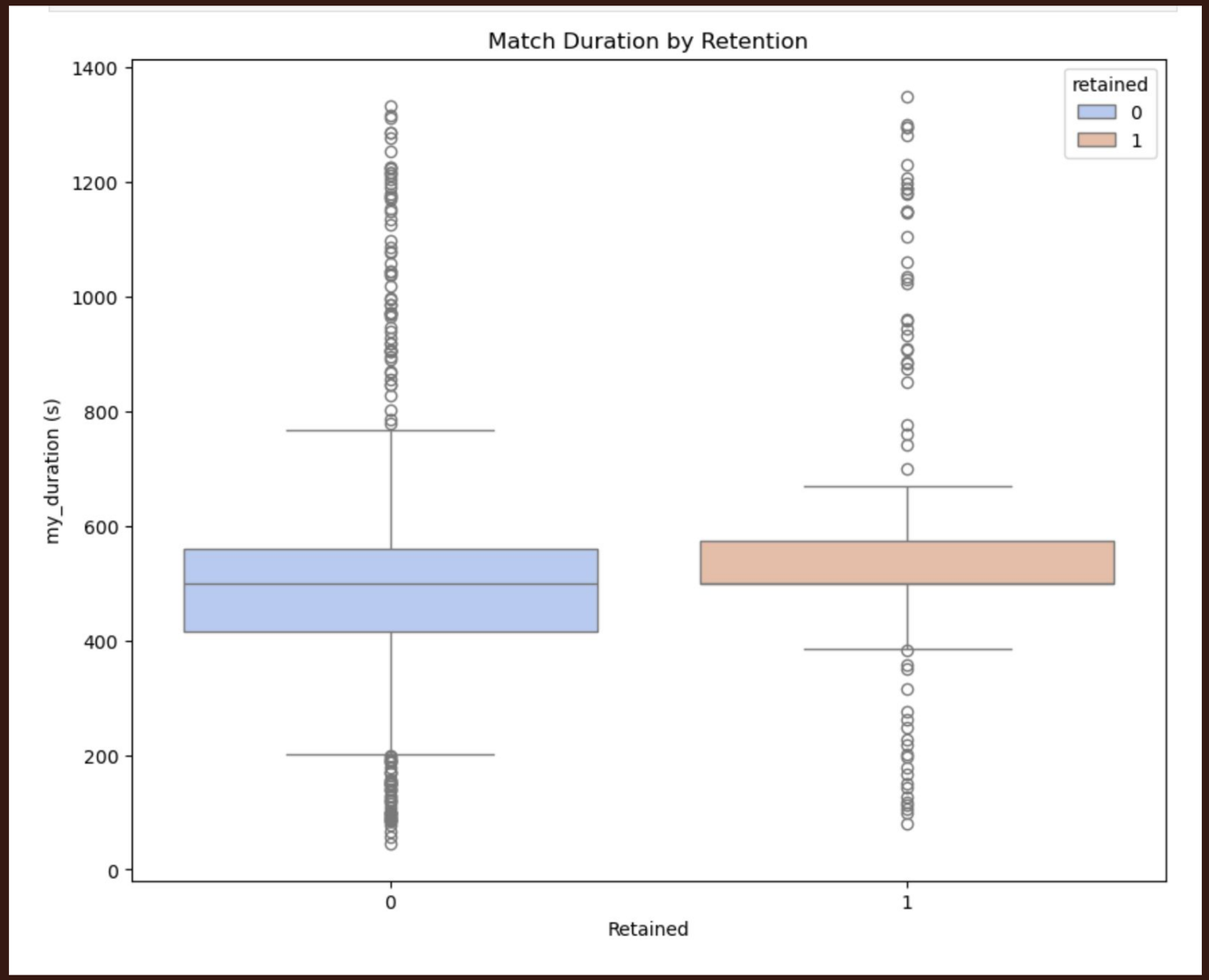
- **Retained:** 145 matches (29%)
- **Churned:** 354 matches (71%)

Correlation Heatmap: EDA



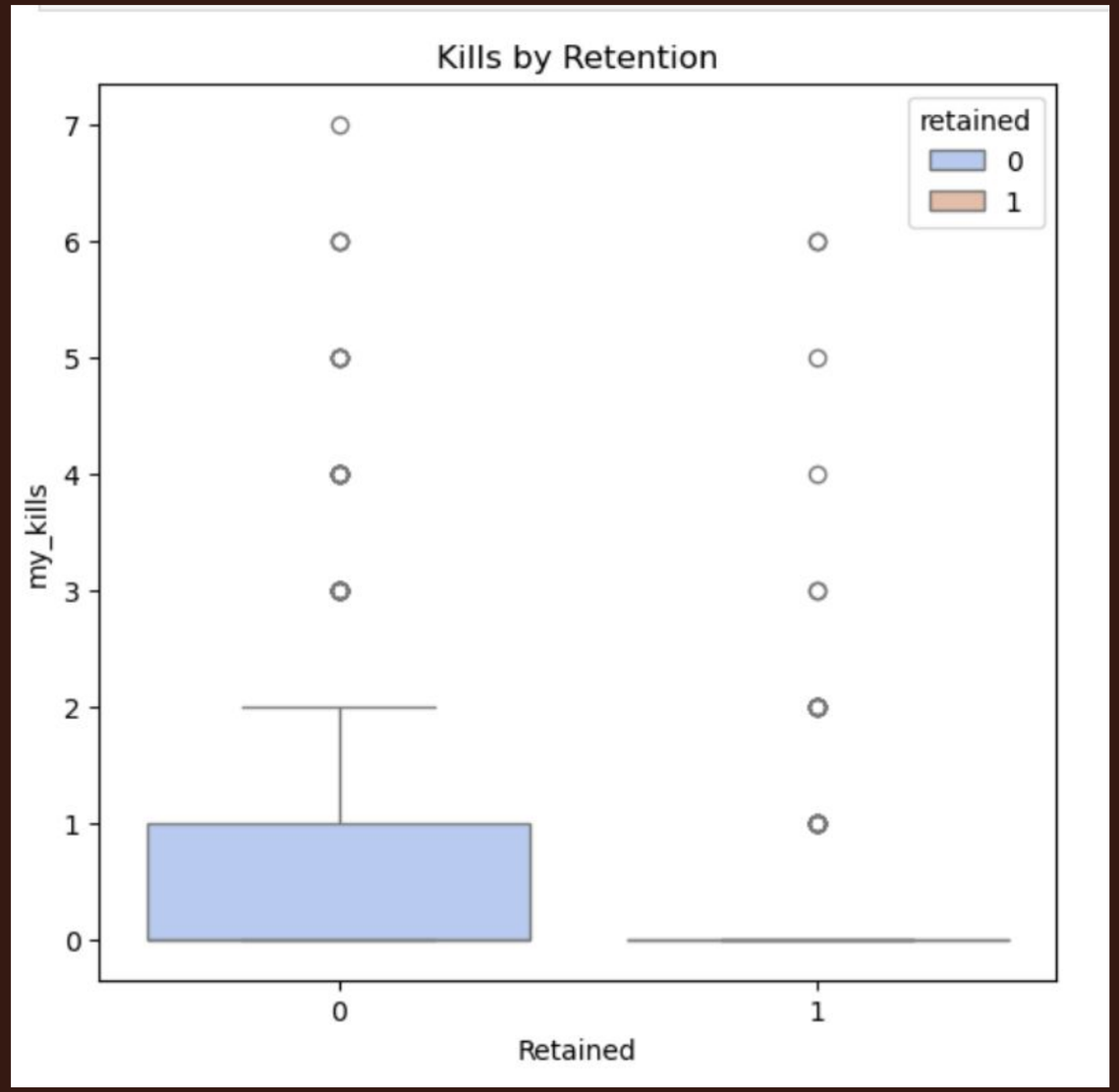
- **Key features: my_duration, my_damage, my_kills**
- **Top pair: my_kills vs my_knocks - r ≈ 0.94**
- **Supporting: my_duration vs my_damage → r ≈ 0.71; my_revives vs my_knocks → r ≈ 0.42**

Match Duration by Retention: EDA



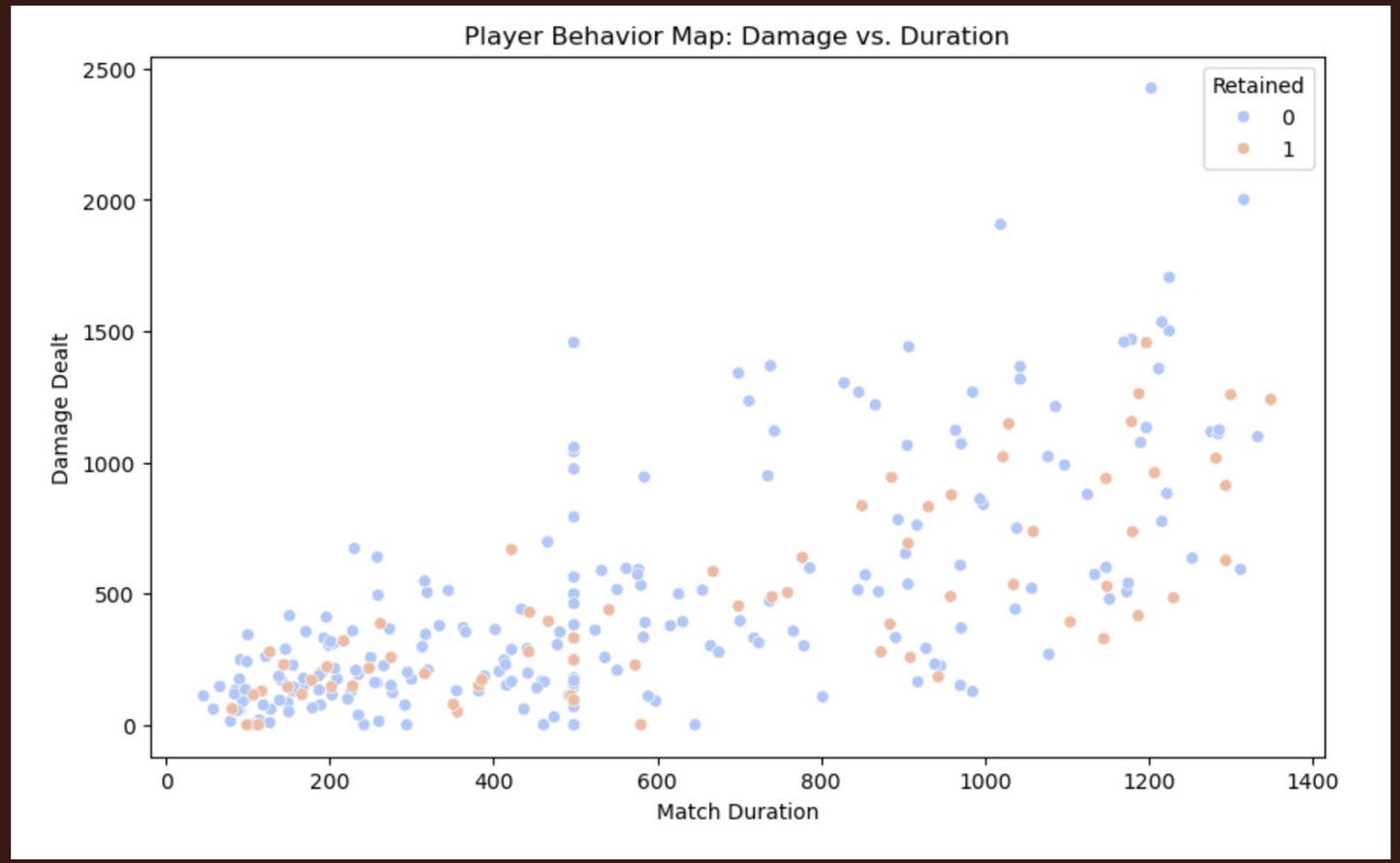
- **Retained (1): higher mean session length; median ≈ 498 s**
- **Churners (0): distribution shifted shorter; fewer long sessions**
- **Model input: my_duration (s), standardized with other numeric features**

Kills by Retention: EDA



- **Medians:** both groups = **0**
- **Means:** churners (0) **0.61** > retained (1) **0.40**
- **Model input:** my_kills (per match), standardized

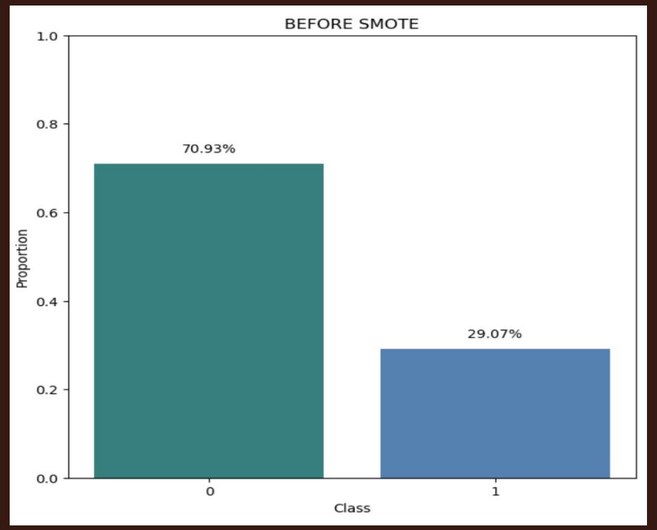
Damage vs Duration: EDA

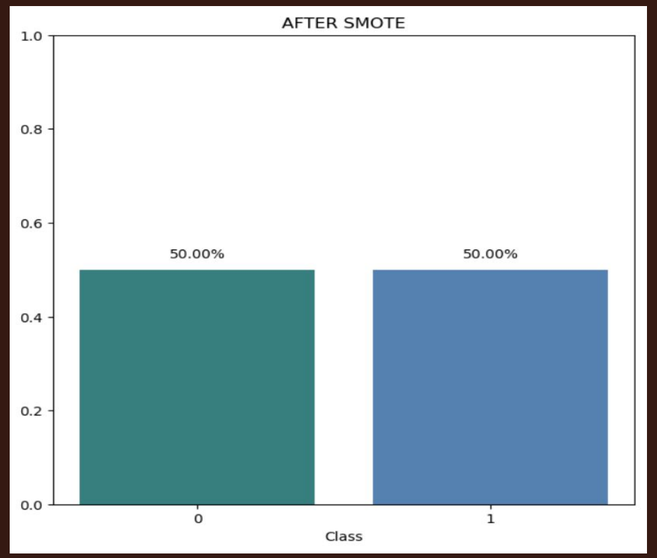


- **Features: my_duration (s), my_damage**
- **Relationship: strong positive correlation ($r \approx 0.71$)**
- **Pattern: longer matches → more damage; labels overlap (no single-threshold rule)**

Pre-Match Tune-up: Preprocessing

- **Train/Test:** stratified 80/20 (X_train 399, X_test 100)
- **Encode:** one-hot categoricals (drop_first), align test to train schema
- **Scale:** StandardScaler on numeric columns (post-encoding)
- **SMOTE (LR-only, in-CV):** retained (class 1) lifted ~29% → ~50% in training folds; base train/test unchanged
- **Final matrix:** X_train (399, 114) · X_test (100, 114)





Dialed In: Tuning & Signals

- **Tuning:** 5× CV + SMOTE (LR-only, in-CV); optimize F1

- **LR tuned config:** L1, C=0.1, liblinear, class_weight=None

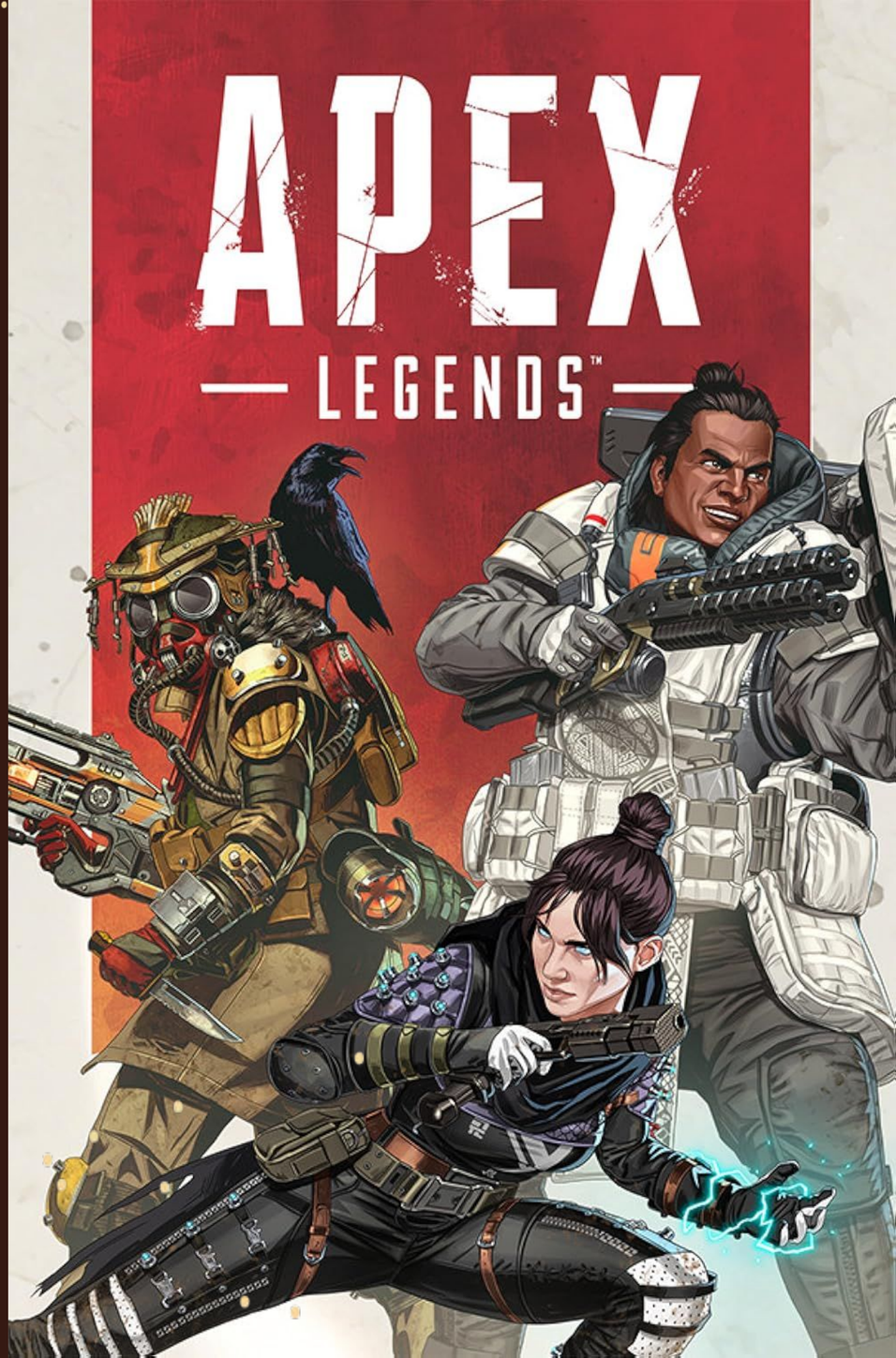
- **Top signals (effect on churn risk):**
  - Monday play pattern — increases risk *(coef +0.127)*
  - Teammate legend: Horizon — increases risk *(coef +0.076)*
  - Revives — increases risk *(coef +0.070)*
  - Assists — decreases risk *(coef −0.133)*
  - Teammate knocks — decreases risk *(coef −0.099)*

Final Model Shoot-out

Model	F1	PR AUC	ROC AUC	Precision	Recall	Accuracy
Logistic Regression — tuned	**0.471**	**0.304**	**0.516**	**0.311**	**0.966**	**0.370**
Logistic Regression — baseline	0.315	0.285	0.397	0.233	0.483	0.390
XGBoost (current)	0.269	0.288	0.492	0.304	0.241	0.620
Random Forest (current)	0.237	0.255	0.413	0.233	0.241	0.550
XGBoost — simple baseline	0.157	0.260	0.441	0.182	0.138	0.570
Random Forest — simple baseline	0.000	0.283	0.465	0.000	0.000	0.660

Early Radar: Can Churn Be Predicted a Week Out?

- **Winner:** Logistic Regression (L1), tuned
- **Why it wins:** Recall-first early warning; interpretable; simple to ship.
- **Hold-out results:** Recall 0.97 *(F1 0.47)* on the 7-day churn label.
- **What it enables:** Nightly risk list for Live-Ops; coefficients make nudges explainable.



The Playbook: Flag → Nudge → Retain

- **Targeting:** Threshold from precision–recall (PR) curve; prioritize lower assists/knocks and a Monday spike.
- **Timing:** Nudge at 5–6 idle days (just before the 7-day label).
- **Tactics:** Reminders, squad-up/assist challenges, Limited-Time Modes (LTMs) surfacing, rank-placement prompts.
- **Guardrails:** Outreach cap, cooldowns, max touches/week.
- **Learning loop:** Log actions→outcomes; weekly precision/recall review; monitor drift, refit each season, A/B test nudges.