Ravenstack Churn Prediction Analysis

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1 Technical Methodology

1.1 Objective

To identify leading indicators of customer churn and build a predictive model to flag at-risk accounts ahead of time using customer, product usage, and support datasets.

1.2 Data Sources

We combined the provided CSV files to construct a unified customer activity model:

- **accounts.csv**: Industry, region, signup details
- **subscriptions.csv**: Plan tier, seats, MRR changes
- **feature_usage.csv**: Daily feature usage across product functions
- **support_tickets.csv**: Customer support volume, SLA breaches
- **churn_events.csv**: Account churn dates and reasons

1.3 Label Definition

Binary classification target:

$$\text{churn\_next\_30d} = \begin{cases} 1 & \text{account churns within next 30 days} \\ 0 & \text{otherwise} \end{cases}$$

1.4 Feature Engineering

We built a daily account panel and aggregated to weekly frequency. Key feature categories:

- **Usage Intensity:** weekly events, 4-week events, usage momentum
- **Engagement Recency:** weeks since last product use or support interaction
- **Support Friction:** tickets in 4 weeks, SLA breaches
- **Commercial Signals:** seats, weekly seat change, MRR
- **Stability:** errors in rolling window

1.5 Modeling Approach

- Time-based split (*train: before 2024-10-01, test: after*)
- Gradient boosting classifier (XGBoost fallback: HistGradientBoosting)
- Class imbalance handled with scale_pos_weight
- Eval metrics: AUC, AUPRC, Precision@K

1.6 Results

Metric	Score
AUC	0.6264
AUPRC (vs. base 0.0482)	0.0875
Precision@Top 10%	0.1204

Table 1: Weekly Model Performance

Performance shows ∼1.8x lift vs. baseline churn rate.

1.7 Top Predictive Signals

1. Weeks since last product use
2. Weeks since last support interaction
3. MRR level
4. Seat count and weekly seat change
5. 4-week usage volume
6. 4-week ticket volume
7. Usage momentum (decline)

These signals typically appear 4–8 weeks before churn.

2 Stakeholder Summary

2.1 Headline

We can identify churn risk **2x better than random**, allowing proactive outreach and retention plays.

2.2 Top Feature Signals

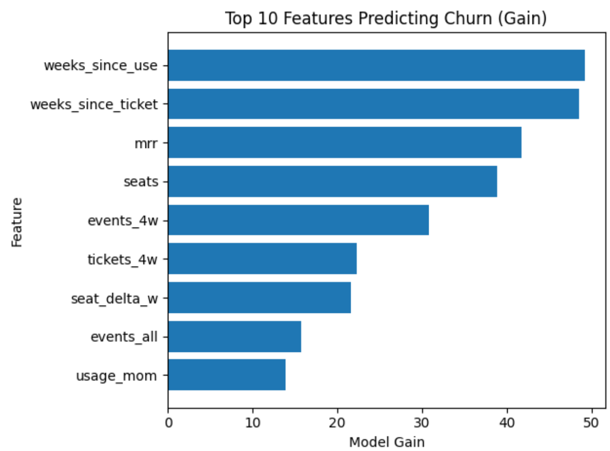

Figure 1: Top 10 features predicting churn

2.3 Key Insights

- **Disengagement drives churn**: inactivity > 2 weeks is the strongest signal.
- **Seat reduction precedes churn**: declining seat usage is an early warning.
- **Silent churn exists**: accounts without support touchpoints quietly leave.
- **Support friction matters**: ticket spikes + no follow-up = higher churn risk.
- **High-value accounts require attention**: lost seats in high-MRR accounts are costly.

2.4 Recommended Actions

2.5 Next Steps

- Deploy churn risk dashboard in CS CRM
- In-app nudges for idle users
- Automated alerts on seat loss trends
- Incorporate sentiment from support ticket text

Trigger	Playbook
>2 weeks since usage	CSM outreach + product re-engagement workflow
Seat drop detected	Value review and right-sizing conversation
Ticket spike or SLA breach	Escalate support + recovery communication
Low product adoption	Enablement + guided onboarding to core features

Table 2: CSM Intervention Strategy

2.6 Business Value

- Increased retention and ARR
- Prioritized CSM workflows
- Reduced “silent churn”
- Clear playbooks tied to measurable leading indicators