



UW x PCTY Capstone Project

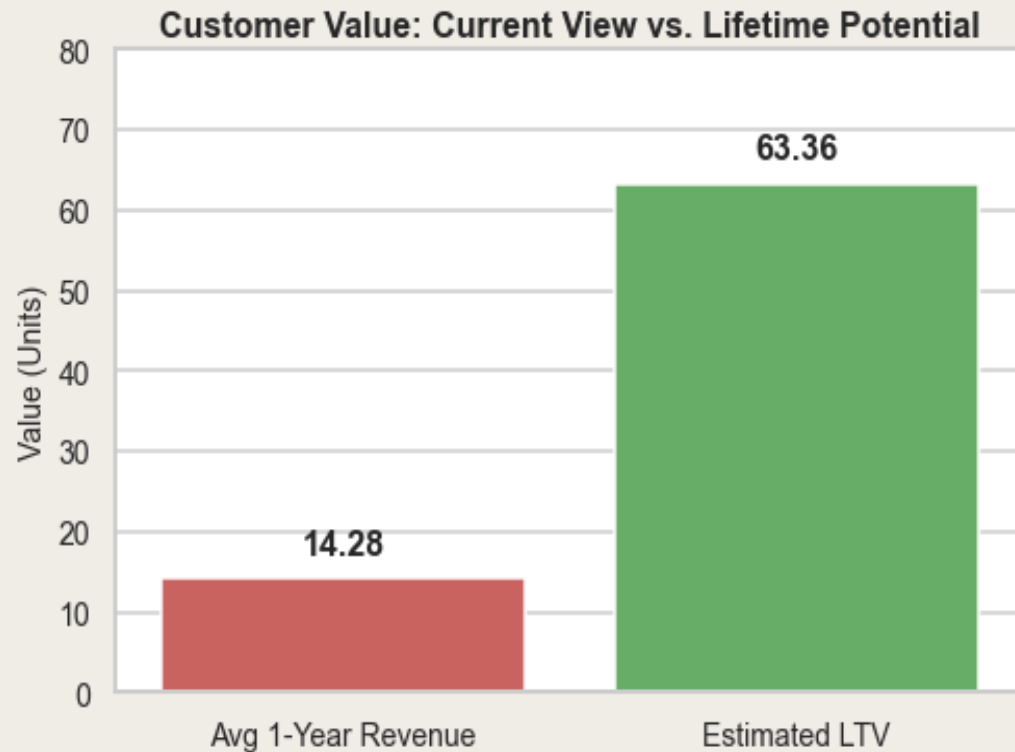
Final Presentation

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WHAT'S THE PROBLEM

The Blind Spot in SaaS Practices

Paylocity's current view of customer value is backward-looking.

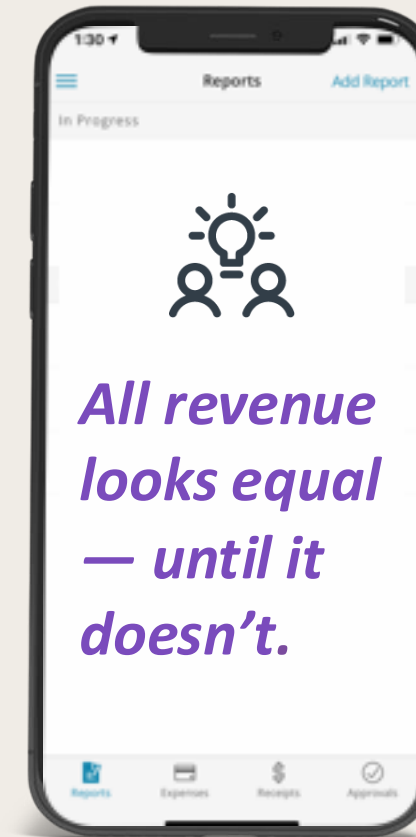


- SaaS companies often know **how much they made**, not **how much value clients still hold**
- Even when using LTV, most rely on **averages** — $\text{ARPU} \times \text{retention}$
- Paylocity makes most decisions based on average **1-year revenue**
- That **downplays retention, growth, and time value of money**

Misallocation Without Forward Value





Same revenue, different lifetime value.

- There's no way to **tell who's high-value vs short-term**
- Resource allocation becomes **guesswork**
- Retention, upsell, and acquisition aren't targeted
- The current model **misses growth signals and customer heterogeneity**



Data Sources Behind the Model

What powers our analysis: 5 years of billing, behavior, and customer profile data

-  **1. Billing Data (NetSuite)**
 - 5 fiscal years of client-level billing
 - Reflects **cash flow**, not booked revenue
 - *Note: Excludes child-parent mapping (reseller/partner level)*
-  **2. Client Profiles (Salesforce)**
 - Segment, Employee Count, Industry, Region
 - Used for segmentation and CAC estimation
-  **3. Account Health (Salesforce)**
 - 5 years of status data (Green / Yellow / Red / Grey / Black)
 - Used to infer retention risk and model churn patterns
-  **4. CAC Estimates (Provided)**
 - Segment-level CAC based on **lead → close rates**
 - *Benchmark only — not actual spend*

HOW WE APPROACHED IT

What's the Problem

How We Approached It

What We Discovered

How It Drives Strategy

A Behavior-Driven Pipeline

From revenue tracking → to value forecasting

$$LTV = \text{annual margin} \cdot \frac{1 + WACC}{1 + WACC - r(1 + g)}$$

- We modeled clients' **actual behavior**
- No more one-size-fits-all

**Behavioral
Signals**

**Predicted
Lifespan**

**Retention
Rate**

Clustering

Growth Rate

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What's the Problem



How We Approached It



What We Discovered



How It Drives Strategy

Modeling Retention — Predicting How Long Clients Stay

Retention is derived, not assumed

The Problem We Faced

- Multi Collinearity
- Limited features
- Low predictive value
- No access to behavioral logs
- Missing transactional signals
- Lacked engagement metrics

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What's the Problem

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Modeling Retention — Our Feature Engineering Solution

If we can't measure behavior directly, let's infer it from what we do have

Engineered Feature	Meaning	Main Source Field
+ cross_sell_count	<i>Times the client adopted new product lines</i>	product_group
+ cross_sell_yr_count	<i>Yearly frequency of cross-sell behavior</i>	product_group
📈 upsell_count	<i>Times the client upgraded within a product</i>	product_group
📈 upsell_avg_growth	<i>Average upsell growth over 5 years</i>	product_group
🔄 recurring_ratio	<i>% of billing that's subscription-based</i>	line_type
⚠️ risk_score	<i>Weighted churn risk from health trajectory</i>	health_status

💡 The Result

Transformed weak profile signals into strong predictive features

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Modeling Retention — Feature Importance (XGBoost) Top 5

What features impacting the model performance?

Predicting Power:

Profile

<

Behavior

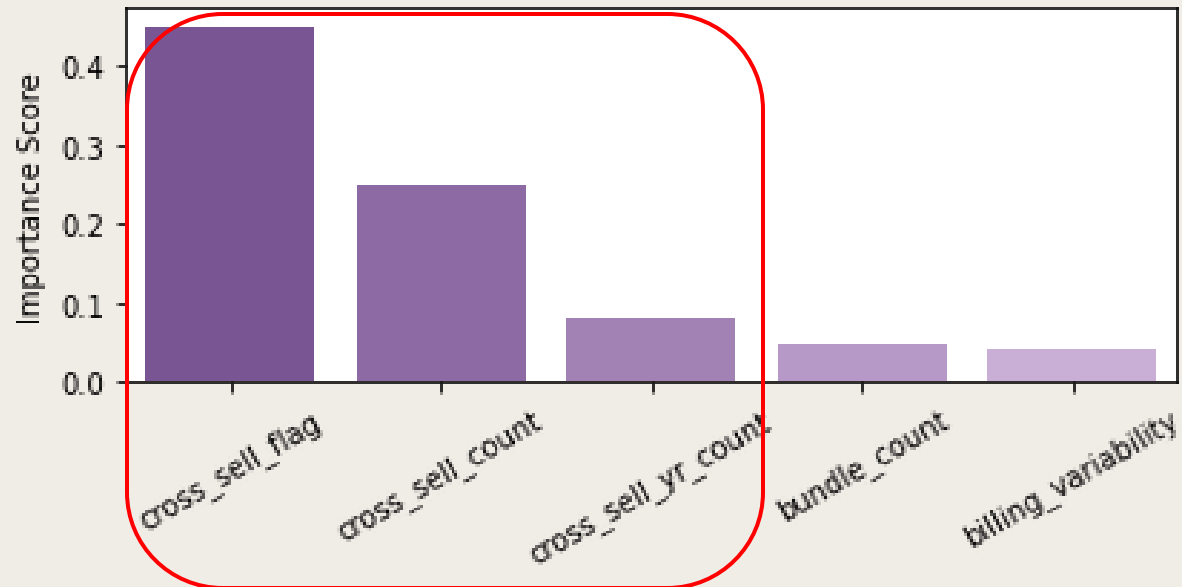
Headcount

Industry

Cross-sell

Subscription

Health



Cross-selling features altogether explain over 75% variance

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Modeling Retention — Results & Performance

How Did Feature Engineering Boost Performance?

Model	R ² Before FE	R ² After FE	Impact of FE
OLS	-	0.471	Strong
Ridge	0.0618	0.4711	8x Better
XGBoost	0.2344	0.6812	3x Better

Feature Engineering

✓ Key success:

Feature engineering increased model performance 8x for Ridge and 3x for XGBoost, proving that creative data engineering can overcome behavioral data limitations and deliver actionable business intelligence.

What's the Problem



How We Approached It



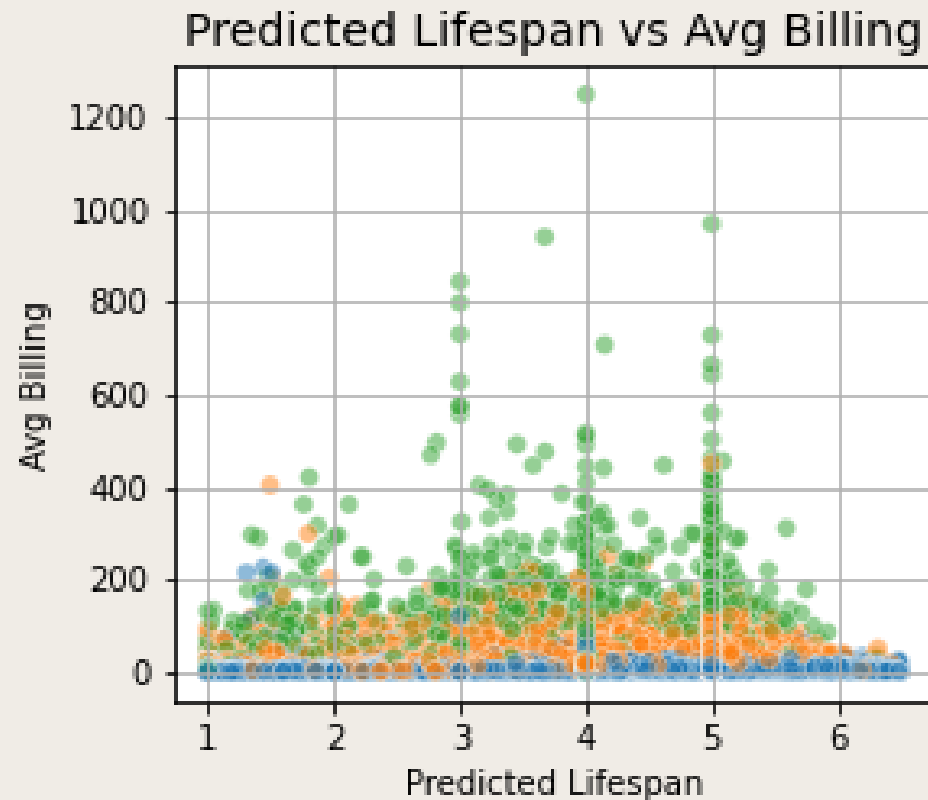
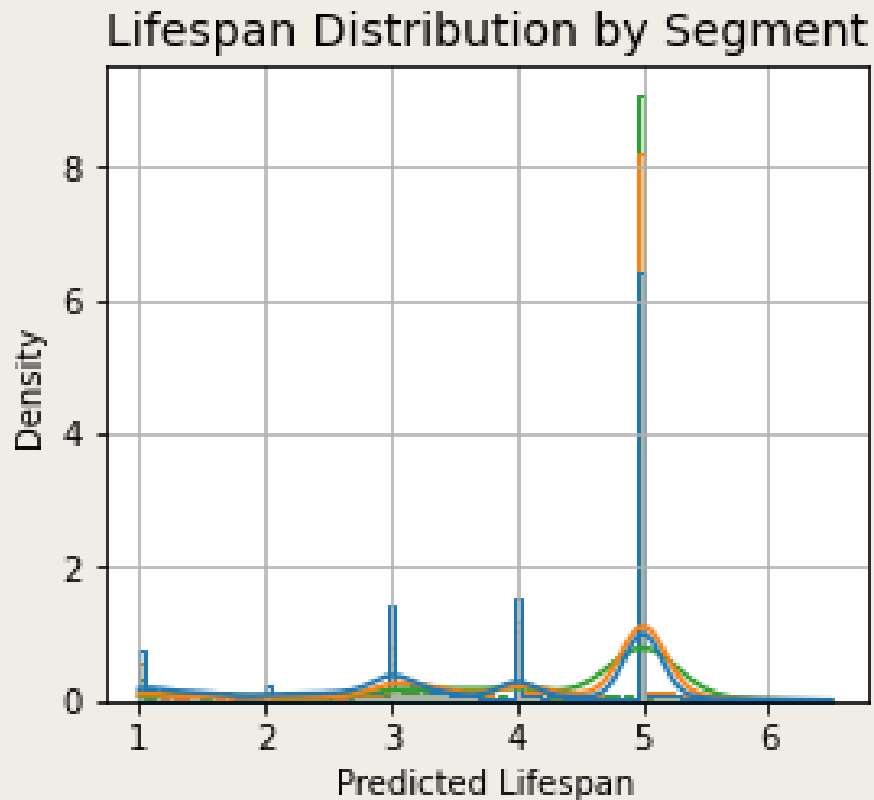
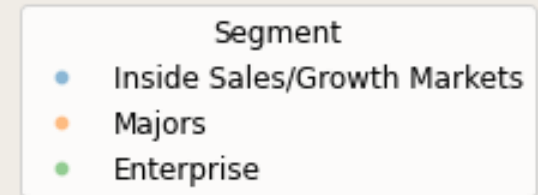
What We Discovered



How It Drives Strategy

Retention as a Value Signal

Predicted Lifespan Patterns and Their Billing Impact Across Segments



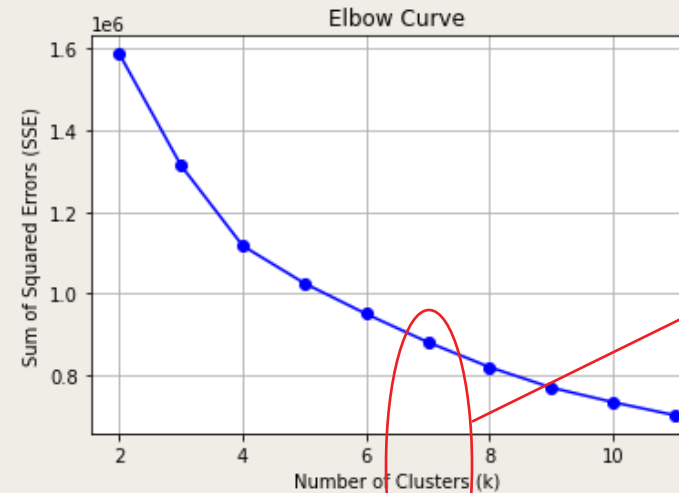
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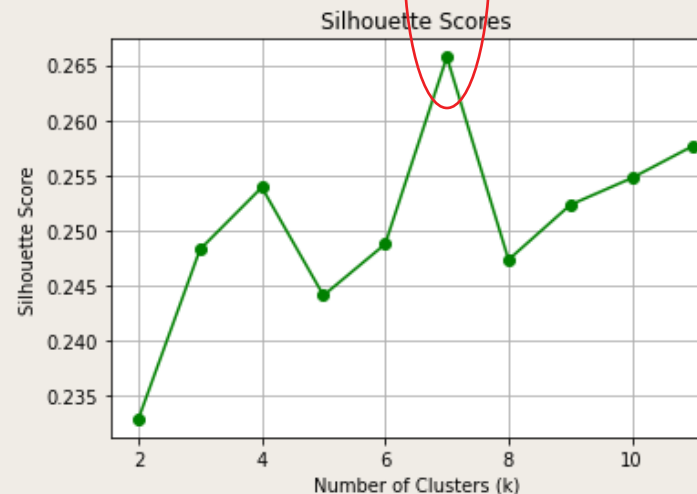
Growth Assignment – Based on Cluster Behavior, Not Heuristic

Growth isn't adjusted based on heuristic rules — it adapts to cluster performance

- All clients start with baseline growth rate 4.4% (inflation)
- We used **KMeans++** to cluster clients (**k = 7**) based on behavioral and billing features
 - Clustering quality was validated using **Elbow** and **Silhouette** methods



7 clusters offered the best balance of compactness and separation.

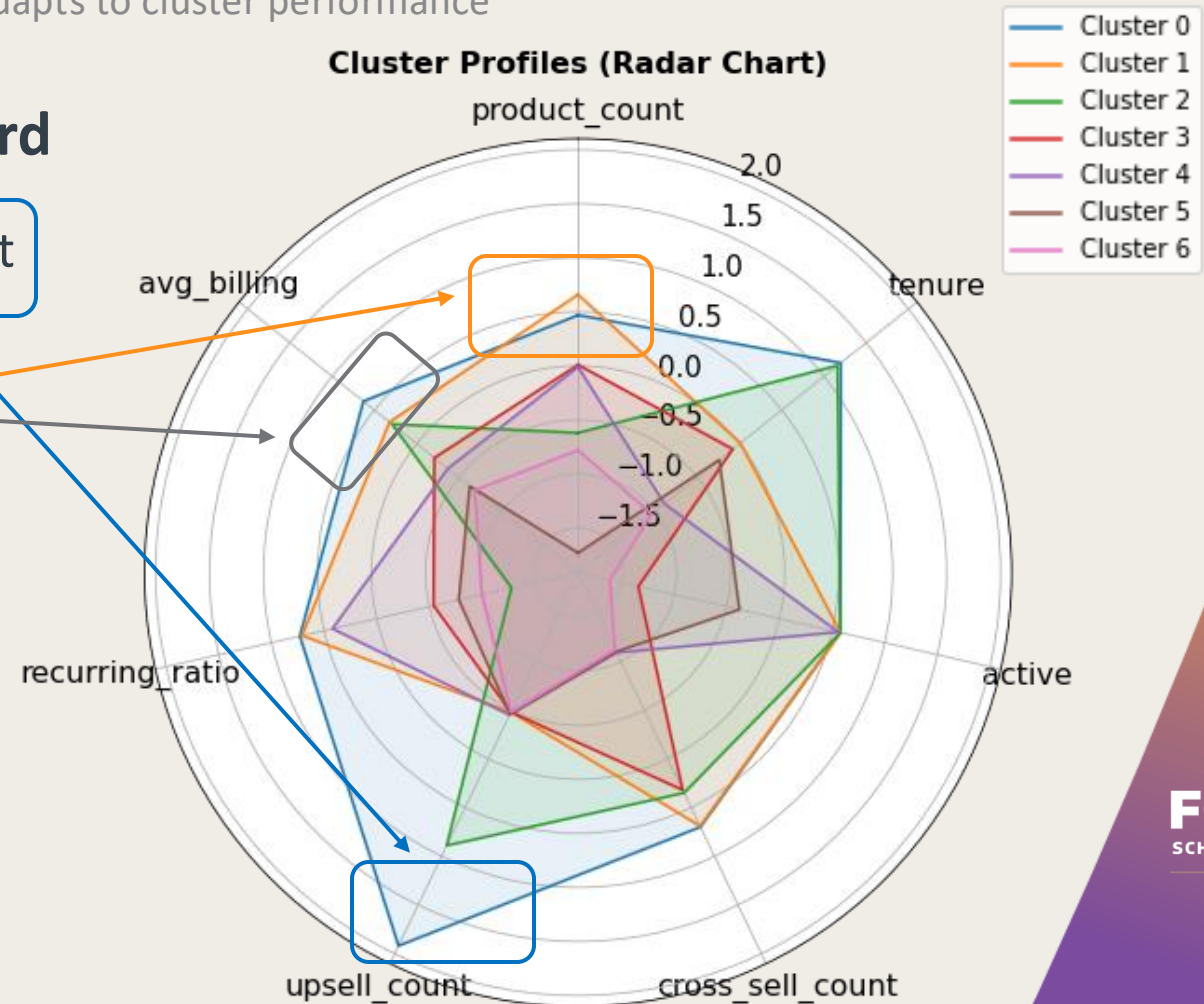


Growth Assignment – Based on Cluster Behavior, Not Heuristic

Growth isn't adjusted based on heuristic rules — it adapts to cluster performance

For select clusters, we **adjust upward**

- **Cluster 0:** High Billing + High Engagement
- **Cluster 1:** High Billing + Broad Usage
- **Cluster 4:** New & Active



Growth Assignment – Based on Cluster Behavior, Not Heuristic

Growth isn't adjusted based on heuristic rules — it adapts to cluster performance

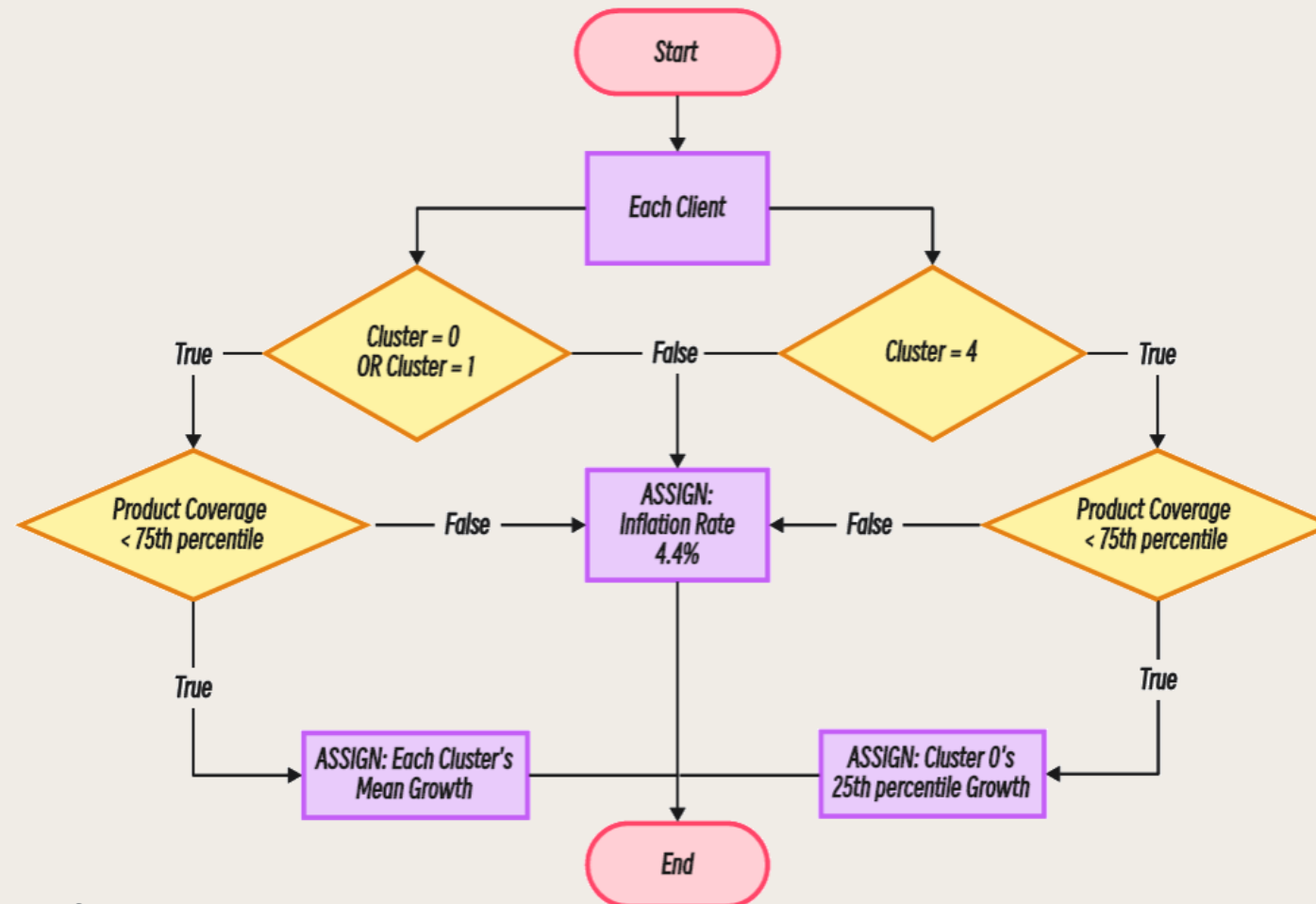
For select clusters, we **adjust upward**

- **Cluster 0:** High Billing + High Engagement
- **Cluster 1:** High Billing + Broad Usage
- **Cluster 4:** New & Active

cluster	0	1	4	2	3	5	6
market_size_mil	1.98	3.18	1.56	1.25	1.38	0.33	1.10
avg_billing	23.31	15.92	6.45	13.98	7.67	6.18	3.88
tenure	5.00	3.18	1.79	4.93	3.03	2.80	1.57
active	1.00	1.00	0.99	1.00	0.16	0.58	0.04
growth	0.20	-0.01	-0.00	0.08	-0.03	-0.00	-0.00
recurring_ratio	0.79	0.78	0.67	0.00	0.29	0.20	0.11
cross_sell_count	3.55	3.47	0.03	2.42	2.10	0.02	0.00
risk_avg	0.84	0.71	0.51	0.69	2.77	0.96	2.68

Growth Assignment – Based on Cluster Behavior, Not Heuristic

Growth isn't adjusted based on heuristic rules — it adapts to cluster performance



- **Adjust ↑ for clients with room to expand**
 - Defined as below the 75th percentile in product coverage
- **If in Cluster 0 or 1**
 - Assigned the cluster's historical **mean** growth
- **If in Cluster 4 (new, active)**
 - Mapped to the **25th percentile** growth of Cluster 0
 - Why? We treat them as early-stage versions of Cluster 0 — with caution
- **All others default to 4.4% baseline (inflation rate)**

WHAT WE DISCOVERED

What's the Problem



How We Approached It



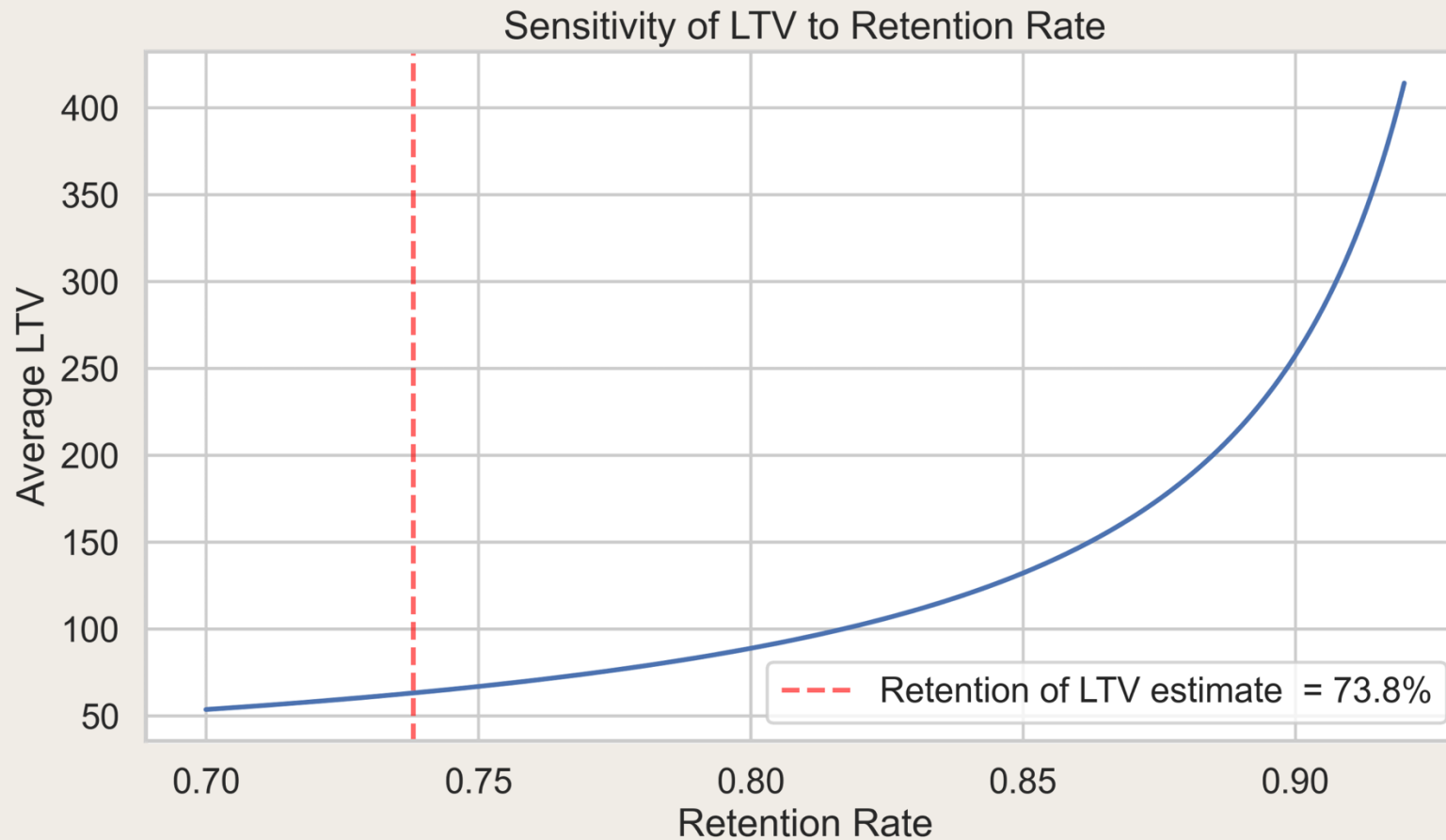
What We Discovered



How It Drives Strategy

Retention Is the Exponential Lever

Small improvements lead to exponential value gain




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Retention Is the Exponential Lever

Small improvements lead to exponential value gain

 **Sensitivity Coefficient** tells us how much LTV changes for a 1% change in the parameter

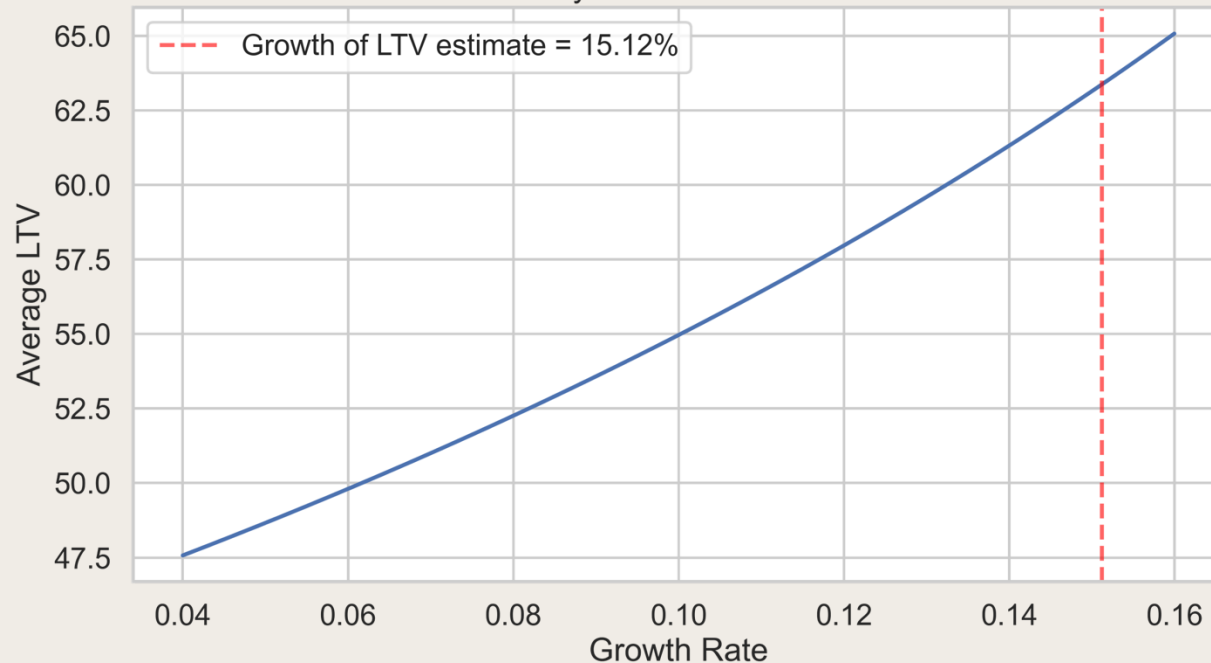
Retention (%)	Average_LTV	Sensitivity	Note
73.8%	63.35	3.43	LTV estimate
85.0%	132.33	8.25	
88.0%	186.81	12.06	
89.0%	216.53	14.14	
92.0%	414.20	27.97	

Why 73.8% retention appears  lower than you might expect?

How Growth Rate (g) Affects LTV

Small acceleration, moderate impact — and it only works if clients stay

Sensitivity of LTV to Growth Rate



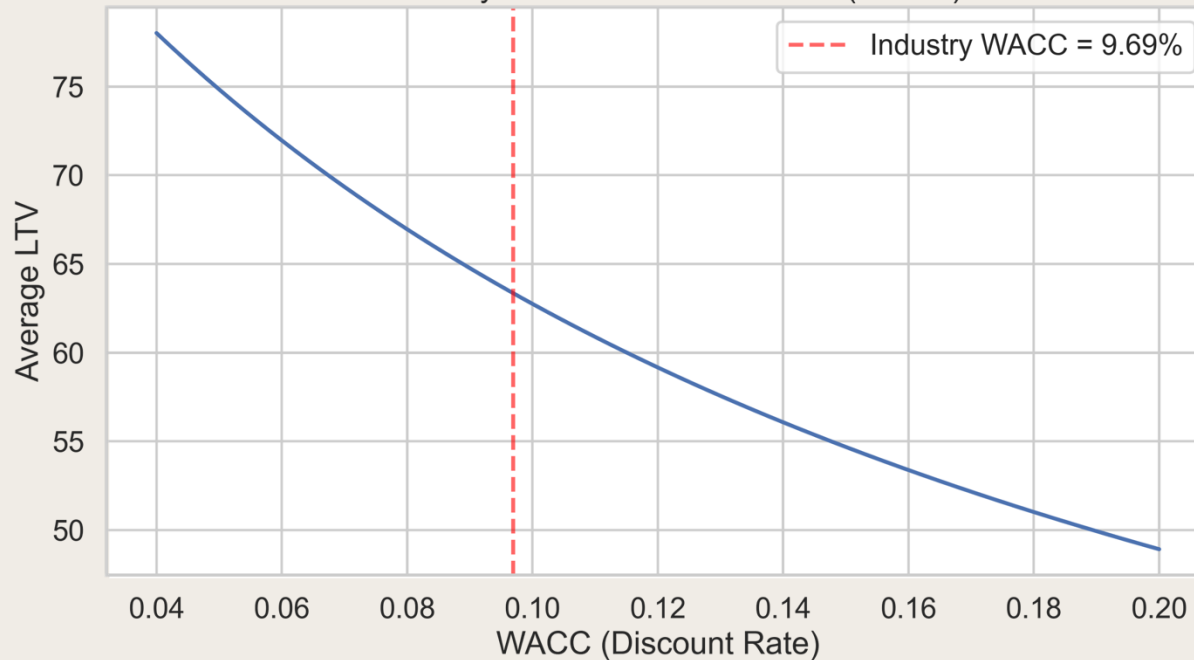
Growth (%)	Average_LTV	Sensitivity	Note
4.4%	48.00	0.10	<i>inflation</i>
13.2%	59.93	0.37	<i>industry average</i>
15.1%	63.36	0.45	<i>LTV estimate</i>
16.0%	65.07	0.49	

$$LTV = m \cdot \frac{1 + i}{1 + i - r(1 + g)}$$

How Financing Cost (*Interest Rate, i*) Affects LTV

An uncontrollable drag — but one we need to plan around

Sensitivity of LTV to Discount Rate (WACC)



Industry Avg WACC:

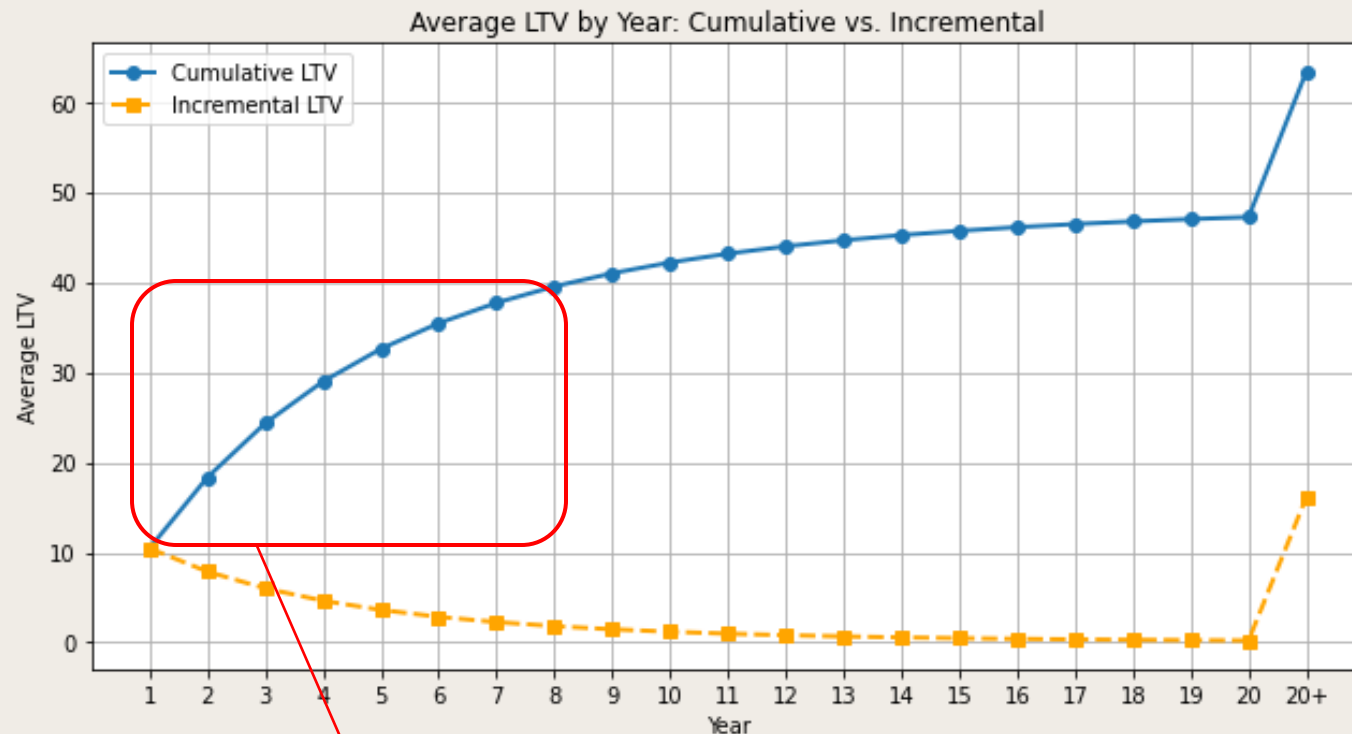
from [NYU Stern / Damodaran](#)

WACC (%)	Average_LTV	Sensitivity	Note
5.00%	74.84	-0.20	
9.69%	63.36	-0.3	industry average
12.00%	59.16	-0.33	
20.00%	48.92	-0.40	

$$LTV = m \cdot \frac{1 + i}{1 + i - r(1 + g)}$$

Retention Builds the Base, Acquisition Extends the Frontier

Retention creates exponential value — but can't fuel growth forever



More than 60% of LTV realized within the first 8 years

- Retention delivers steep value gain in early years
- By year 4, half of LTV has already materialized
- After year 8, marginal value flattens
- New clients are needed to maintain revenue momentum

*Retention creates value.
Acquisition sustains momentum.
You need both!*

Strategic Segments: A Portfolio View of Customer Value

Grouped for clarity — derived from 7 clusters, driven by behavior

strat_seg	1-Prime	2-Loyal	3-Climbers	4-Churning
market_size_mil	2.58	0.79	1.47	1.10
avg_billing	19.62	10.08	7.06	3.88
tenure	4.09	3.86	2.41	1.57
active	1.00	0.79	0.58	0.04
growth	0.10	0.04	-0.02	-0.00
recurring_ratio	0.78	0.10	0.48	0.11
cross_sell_count	3.51	1.22	1.07	0.00
risk_avg	0.78	0.82	1.64	2.68

- We grouped clients into **four strategic segments** to simplify communication and enable business action.
- These segments reflect differences in billing, engagement, risk, and growth potential.
- This heatmap summarizes their key signals — you'll see clear contrasts in billing, tenure, and risk.

⚠ Note: This merge favors clarity. **For actual execution, we recommend operating at the 7-cluster level** to retain granularity.

The “Climbers” segment, for example, combines both high-growth and lower-engagement clusters — hence the dip in active rate

Prime & Loyal: High Value, Low Risk — But Different Plays

Two retaining segments, two very different strategies

- ◆ Prime ($C0 + C1$)
 - High billing, wide product usage, active & loyal
 - Top-tier LTV & engagement — ideal for flagship marketing
 - Strategic moves:
 - Deepen with cross-sell & success teams
 - Feature in **referral & showcase programs**

strat_seg	1-Prime	0	1	
market_size_mil	5.17	1.98	3.18	million ppl (staff)
avg_billing	39.23	23.31	15.92	units
tenure	4.09	5.00	3.18	years
active	1.00	1.00	1.00	%
growth	0.10	0.20	-0.01	%
recurring_ratio	0.78	0.79	0.78	%
cross_sell_count	3.51	3.55	3.47	#
risk_avg	0.78	0.84	0.71	x/4 score

⚠ Note: This merge favors clarity. For actual execution, we recommend operating at the 7-cluster level to retain granularity.

Prime & Loyal: High Value, Low Risk — But Different Plays

Two retaining segments, two very different strategies

- ◆ Loyal (C2 + C5)
 - Passive users, but low churn & stable tenure
 - Low-touch needed — but don't neglect renewals
 - Strategic moves:
 - Low-cost email/drip campaigns
 - Consider **auto-renew** or **passive engagement programs**

strat_seg	2-Loyal	2	5	
market_size_mil	1.59	1.25	0.33	million ppl (staff)
avg_billing	20.16	13.98	6.18	units
tenure	3.86	4.93	2.80	years
active	0.79	1.00	0.58	%
growth	0.04	0.08	-0.00	%
recurring_ratio	0.10	0.00	0.20	%
cross_sell_count	1.22	2.42	0.02	#
risk_avg	0.82	0.69	0.96	x/4 score

⚠ Note: This merge favors clarity. For actual execution, we recommend operating at the 7-cluster level to retain granularity.

Climbers & Churning: Nurture or Exit

Emerging upside — and the warning signs

- ◆ Climbers (C3 + C4)
 - High growth signals — especially in C4
 - But engagement is mixed due to C3's shallow usage
 - Strategic moves:
 - Onboarding optimization, education nudges
 - Set **risk watchlists**, define **reactivation triggers**
 - Experiment with test campaigns or limited offers

strat_seg	3-Climbers	3	4	
market_size_mil	2.94	1.38	1.56	million ppl (staff)
avg_billing	14.12	7.67	6.45	units
tenure	2.41	3.03	1.79	years
active	0.58	0.16	0.99	%
growth	-0.02	-0.03	-0.00	%
recurring_ratio	0.48	0.29	0.67	%
cross_sell_count	1.07	2.10	0.03	#
risk_avg	1.64	2.77	0.51	x/4 score

⚠ Note: This merge favors clarity. For actual execution, we recommend operating at the 7-cluster level to retain granularity.

Climbers & Churning: Nurture or Exit

Emerging upside — and the warning signs

- ◆ Churning (C6)
 - Extremely low activity and poor retention
 - High churn scores, often post-onboarding drop-offs
 - Strategic moves:
 - Exit flow design — offboarding, feedback capture
 - Or experiment with last-touch recovery campaigns
 - Consider reducing CS effort / automating deactivation

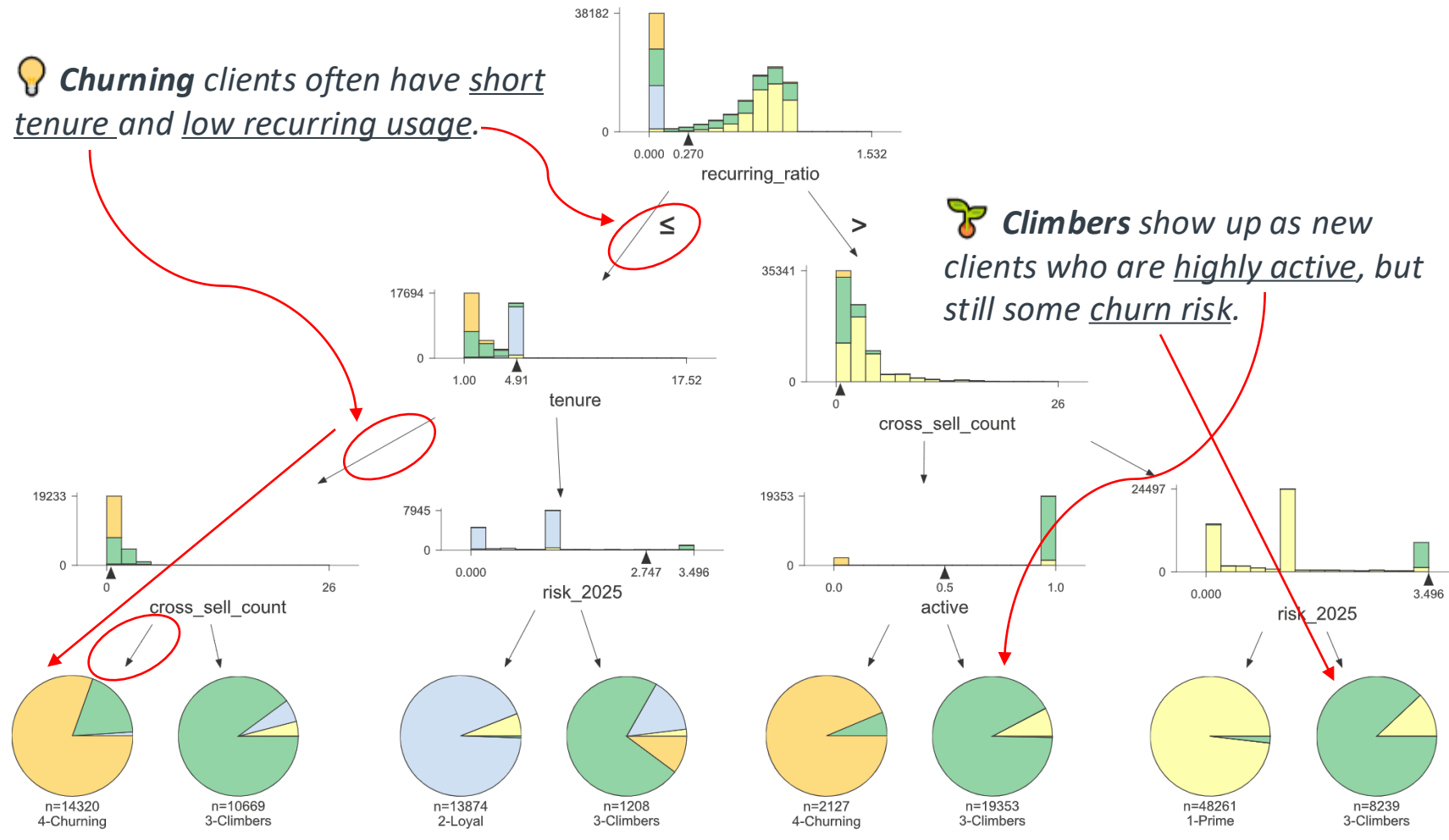
strat_seg	4-Churning	6	
market_size_mil	1.10	1.10	million ppl (staff)
avg_billing	3.88	3.88	units
tenure	1.57	1.57	years
active	0.04	0.04	%
growth	-0.00	-0.00	%
recurring_ratio	0.11	0.11	%
cross_sell_count	0.00	0.00	#
risk_avg	2.68	2.68	x/4 score

⚠ Note: This merge favors clarity. For actual execution, we recommend operating at the 7-cluster level to retain granularity.

Validation with Decision Tree

💡 *Churning clients often have short tenure and low recurring usage.*

🌱 *Climbers show up as new clients who are highly active, but still some churn risk.*



ROI Snapshot: Where Do We Win?

LTV-to-CAC ratios tell us which segments drive profitable growth.
(Based on Paylocity's internal segmentation and CAC assumptions.)

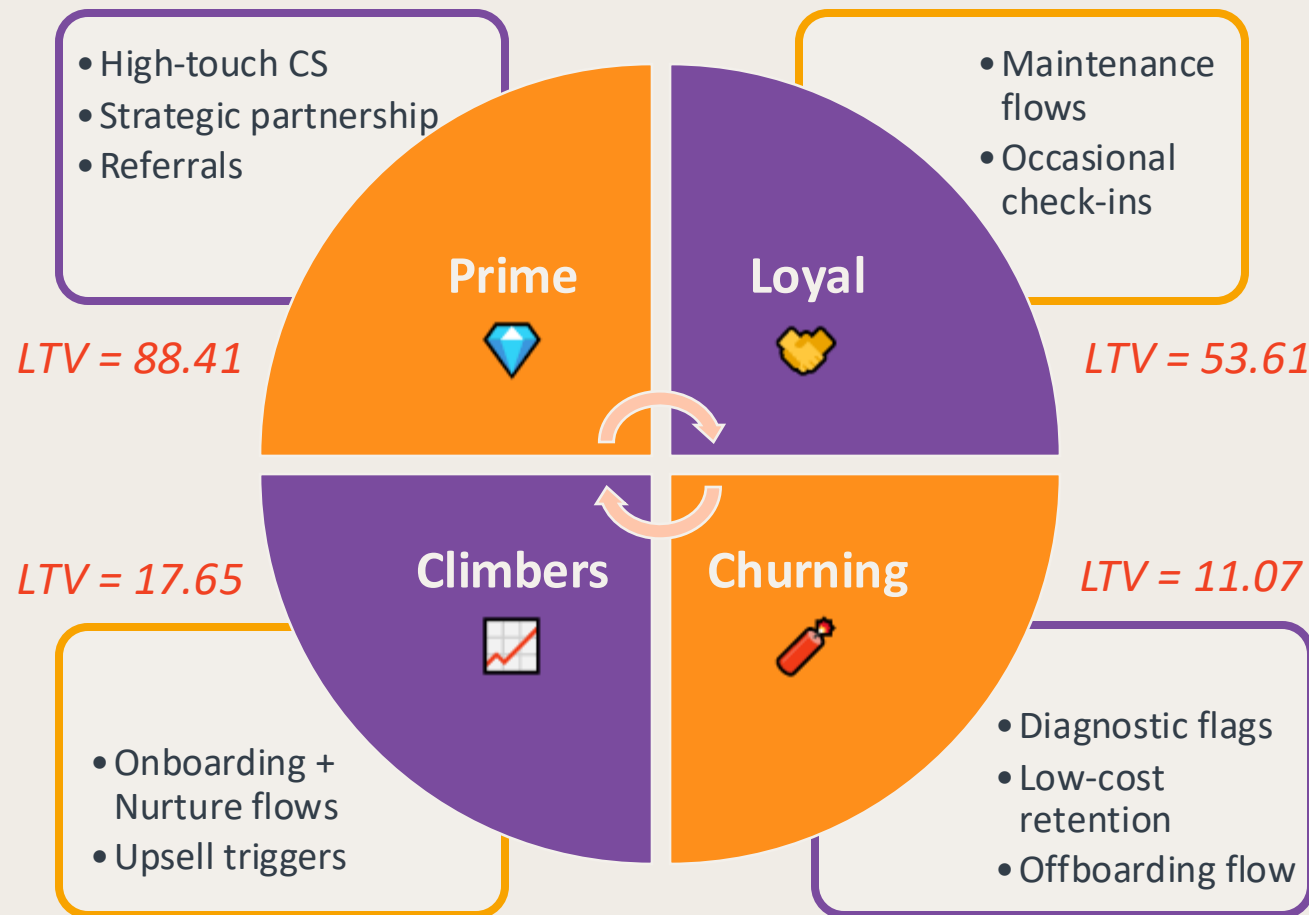
PCTY Segment	Avg LTV	CAC	LTV/CAC
1-Growth	30.48	6.00	5.08
2-Major	167.63	5.01	33.46
3-Enterprise	572.82	14.28	40.11
Total	63.36	6.04	10.49

- **CAC:** Estimated, not modeled — provided by client as rough benchmarks
- Enterprise ROI is exceptional (40x), but accounts for only **16% of billing**
- Growth segment has decent return (5x) — but potential may be capped
- **Takeaway:** Helps **prioritize investment** across segments based on potential payoff

HOW IT DRIVES STRATEGY

Turning Segment Insights into Strategy

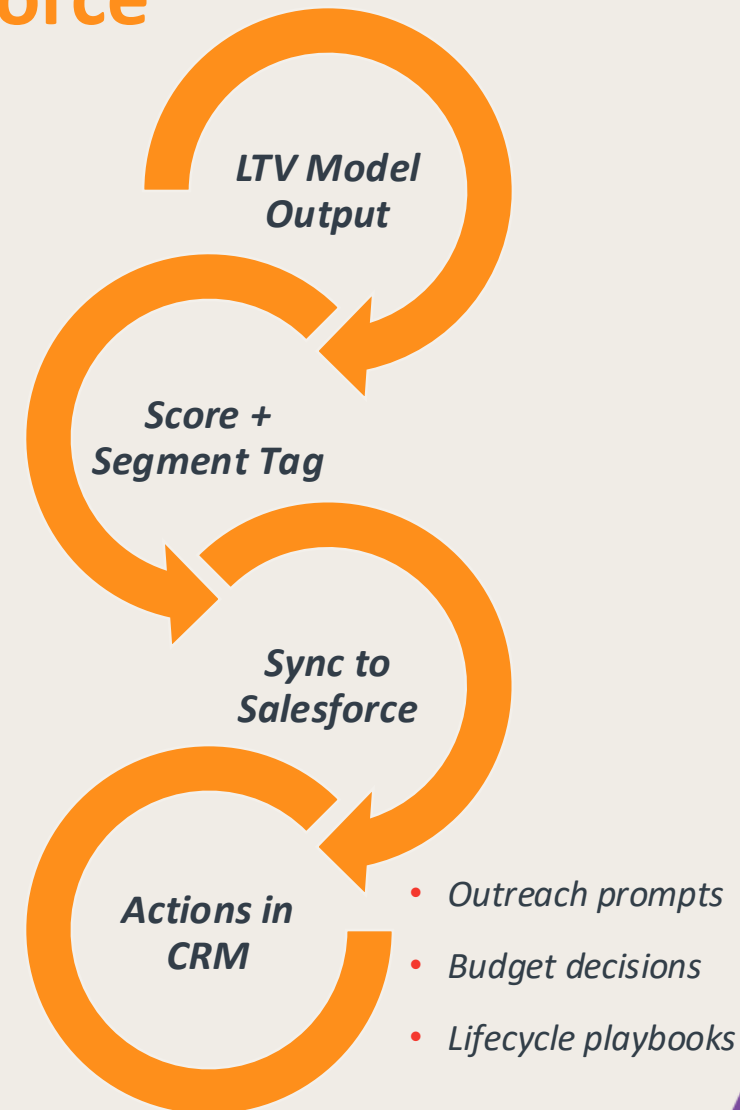
Tailored actions by customer segment to maximize value



Scoring and Prioritization in Salesforce

Using LTV + Retention to guide budget and outreach in real-time

- **Why this matters**
 - Your CRM (e.g., Salesforce) is where reps make day-to-day decisions
 - Embedding LTV + Segment scores = smarter resource allocation
 - Let sales/CS see: *who to focus on, who's at risk, who to grow*
- **What we recommend**
 - Integrate LTV scores and segment labels into Salesforce client records
 - Create workflows that:
 - Flag high-potential climbers for onboarding push
 - Set CS priorities by segment (e.g., Prime = high touch)
 - Trigger retention playbooks for Churning clients



What's the Problem



How We Approached It



What We Discovered

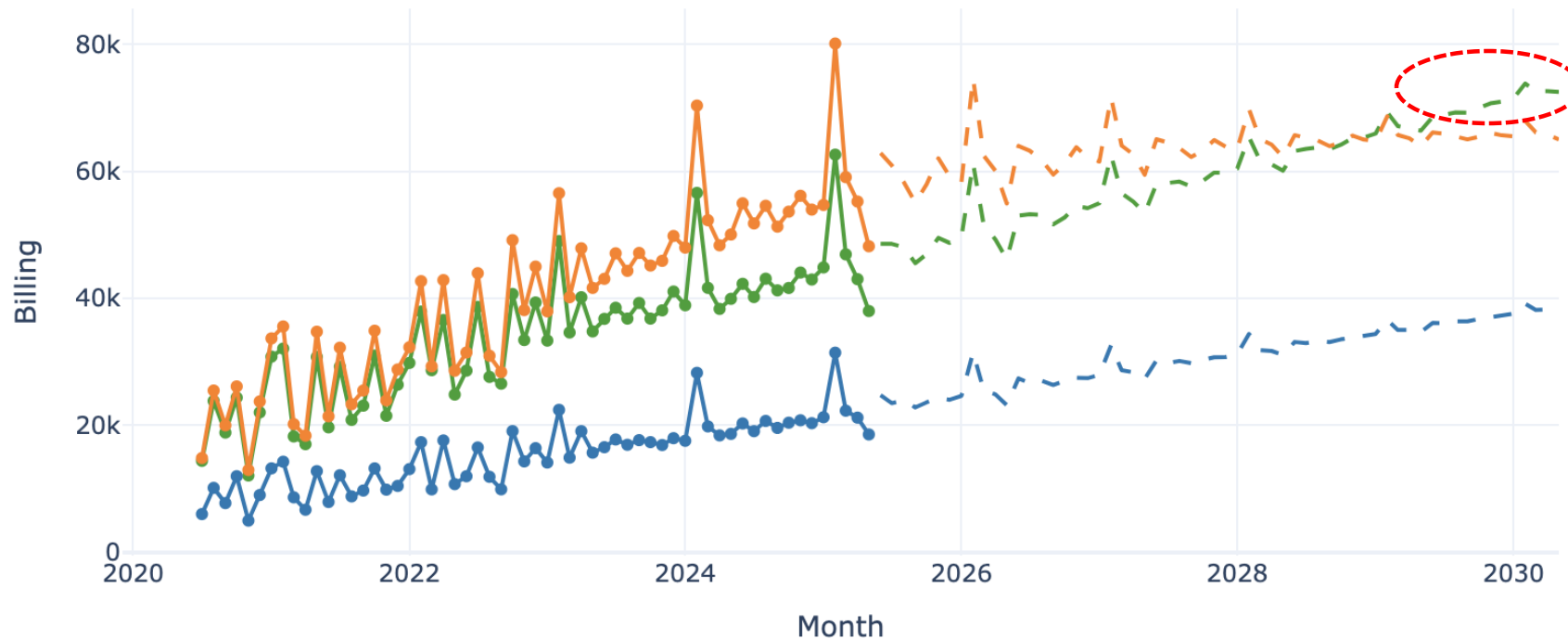


How It Drives Strategy

Bridging Potential and Reality

Comparing long-term LTV potential with SARIMA revenue forecasts

Monthly Billing Forecast by calc_seg (Historical + ARIMA Forecast)



Segment

- 1-Growth - Historical
- 1-Growth - Forecast
- 2-Major - Historical
- 2-Major - Forecast
- 3-Enterprise - Historical
- 3-Enterprise - Forecast

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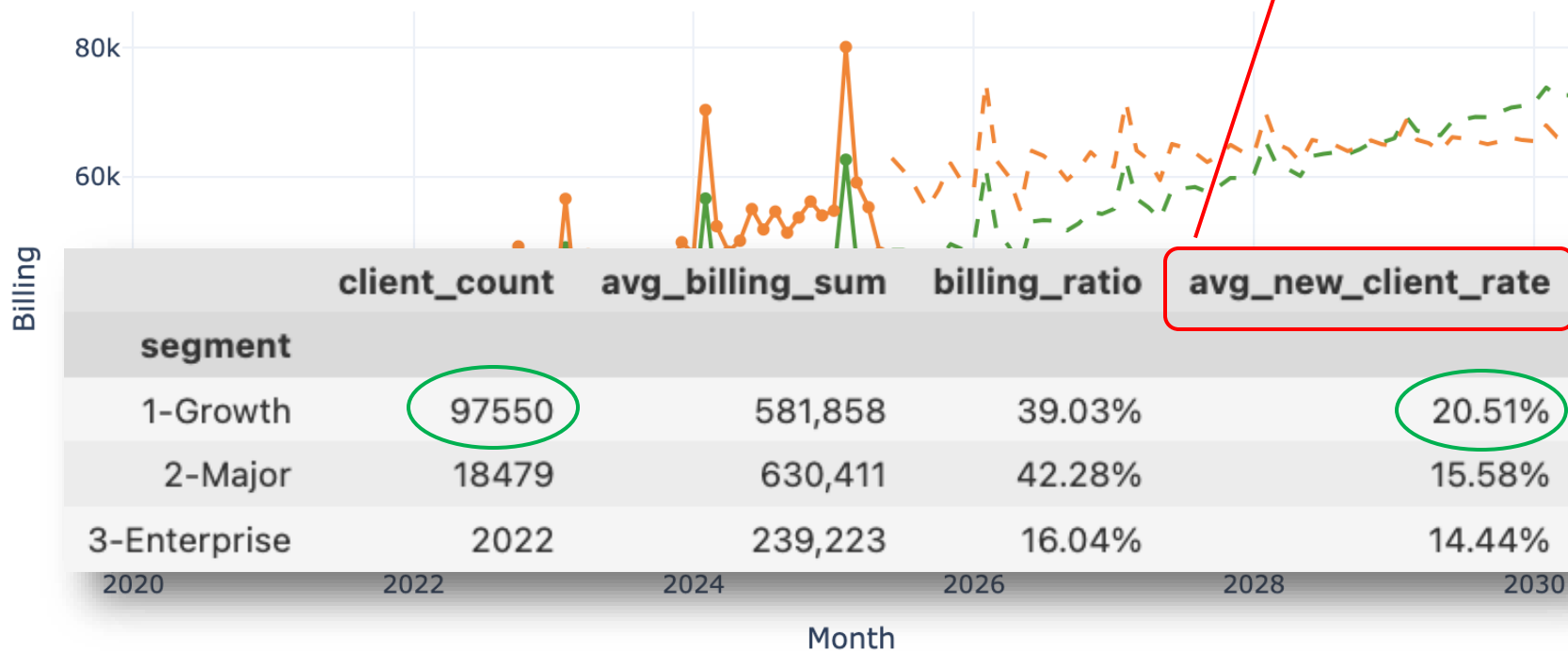
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Bridging Potential and Reality

Comparing long-term LTV potential with SARIMA revenue forecasts

💡 *New client acquisition —
naturally beyond LTV's scope*

Monthly Billing Forecast by calc_seg (Historical + ARIMA Forecast)



Segment




- 1-Growth - Historical
- 1-Growth - Forecast
- 2-Major - Historical
- 2-Major - Forecast
- 3-Enterprise - Historical
- 3-Enterprise - Forecast

QUICK WRAP-UP

Final Takeaways — Turning Insights into Action

Retention protects. Growth extends. Acquisition expands.

$$LTV = \text{annual margin} \cdot \frac{1 + i}{1 + i - r \cdot (1 + g)}$$

-  **Retention protects the core** — most value is realized early
 - Strengthen loyalty (*Prime & Loyal*) and reduce churn through segment-based playbooks
-  **Growth matters — once retention is strong**
 - Expand future stars (*Climbers*) with upsell nudges and onboarding reinforcement
-  **Acquisition expands the frontier** — it's how scale happens
 - Target strategically with *real-time clustering*, not just demographic profiles

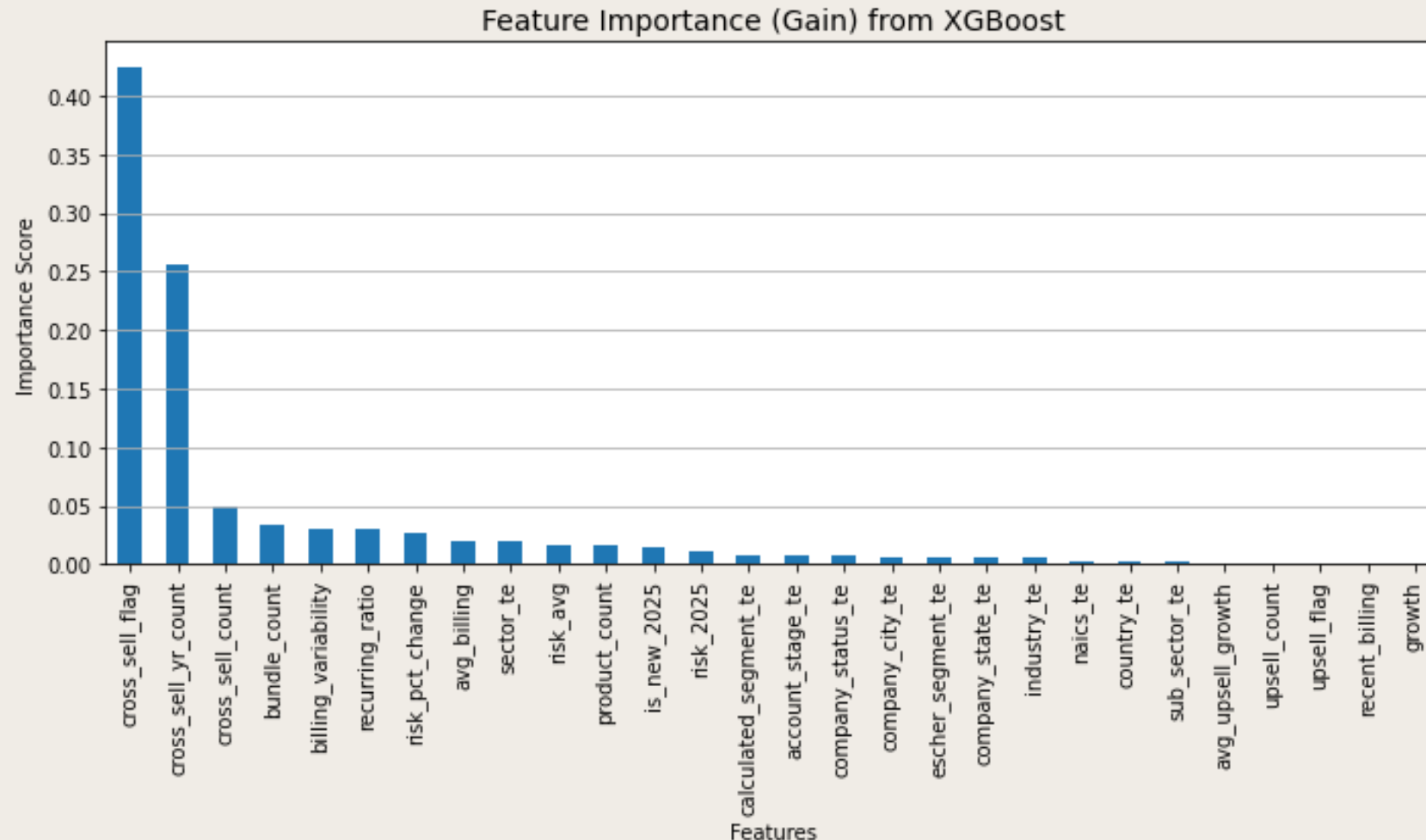


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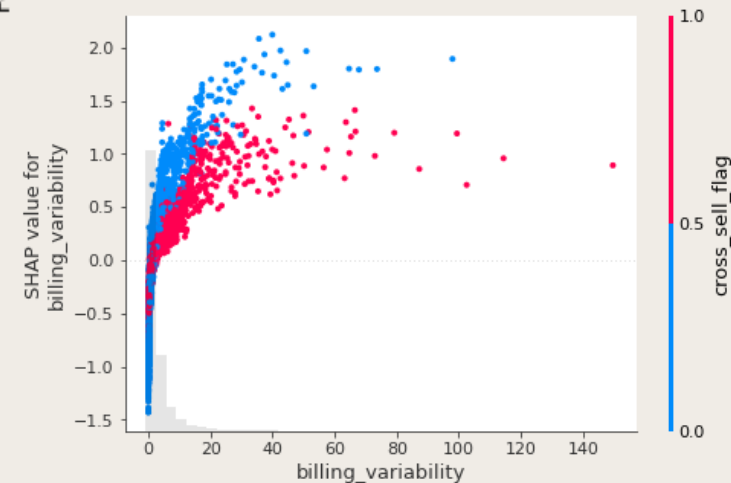
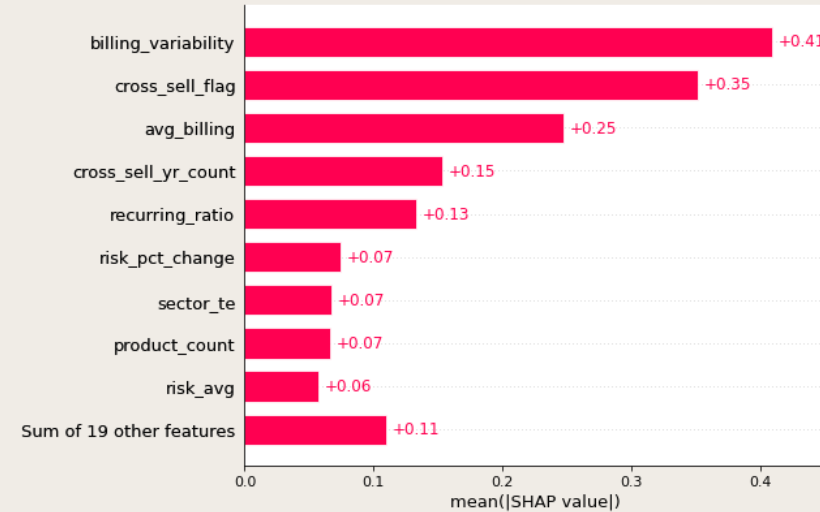
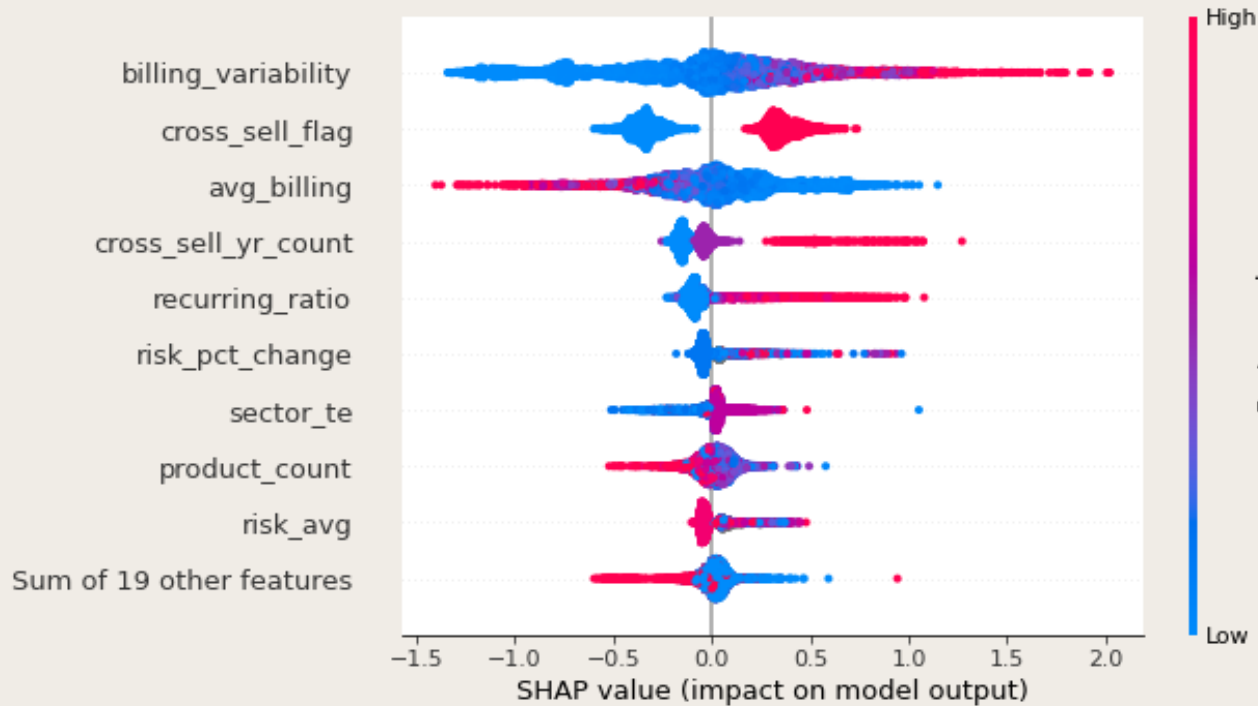
Modeling Retention – Feature Importance (XGBoost)

Top drivers of customer lifespan prediction, ranked by model contribution



Modeling Retention – SHAP Analysis

Explaining the model: how each feature pushes retention predictions up or down



SARIMA Model Selection Summary by Segment

Auto-selected via AIC optimization using 60 months of segment-level billing data

Segment	ARIMA Order	Seasonal Order	AIC	Notes
1-Growth	(3,1,1)	(1,0,0)[12]	1167.56	Acceptable, modest variance
2-Major	(4,1,0)	(1,0,0)[12]	1199.23	Slightly higher, still stable
3-Enterprise	(4,1,1)	(1,0,0)[12]	1082.56	Lowest AIC, most stable model

- We selected the SARIMA configuration for each segment based on the lowest AIC value found via *auto_arima*.
- All models have moderate complexity and include yearly seasonality.
- AIC values range from 1082 to 1199, indicating reasonable fit given the data scale (~60 monthly observations).

SARIMA Residual Diagnostics

Residuals across all segments behave as white noise — no signal left unexplained.

SARIMA Diagnostic – 1-Growth

