TITLE: Lifetime Value Modelling and Targeting Strategy for Python Logistics

Question 1: RFM Model-Based Scoring Criteria

Python Logistics can implement a weighted **RFM (Recency, Frequency, Monetary)** scoring model based on the past **3 months of customer behavior to identify its most valuable supermarket and foodservice clients**. This model is tailored to the logistics sector, where delivery consistency and profitability are critical due to limited truck availability. The model assigns greater importance to **Frequency** and **Monetary value (40 points each)**, as these directly impact route planning and profit margins. **Recency** is weighted lower (**20 points**) because one-off recent orders (e.g., from a new franchisee) don't necessarily indicate long-term value.

- **Recency (20 points):** Reflects how recently a customer ordered. Clients like **Countdown** or **Pak'nSave** that placed orders **within the last 7 days** score highest, reflecting ongoing inventory needs. Longer gaps suggest declining engagement or seasonal demand.
- **Frequency (40 points):** Measures how often a customer orders. Outlets like **KFC** or **McDonald's**, which require **weekly or more frequent deliveries**, show operational reliance and earn the highest scores. Clients ordering less than 3 times are deprioritized as low-demand or opportunistic.
- **Monetary (40 points):** Captures total spend. Supermarkets generating **$125,000+** in logistics revenue deserve premium attention due to their contribution to cash flow. Chains like **Woolworths** may fall into this tier due to bulk regional shipments.

Parameter	Criteria	Score	Weight
Recency(R)	0–7 days since last order	20	20
	8–14 days	15	
	15–30 days	10	
	31–60 days	5	
	61–90+ days	0	
Frequency (F)	15+ orders in last 3 months	40	40
	10–14 orders	30	
	6–9 orders	20	
	3–5 orders	10	
	0–2 orders	0	
Monetary (M)	$125,000+ in revenue	40	40
	$75,000 – $124,999	30	
	$40,000 – $74,999	20	

	$15,000 – $39,999	10	
	Below $15,000	0	

Table 1: Weighted RFM Scoring Matrix

Question 2: Using Choice Models for Granular Targeting

While the RFM model provides a solid foundation for segmenting customers, Python Logistics can adopt **choice models** such as **logistic regression** or **multinomial logit** to predict the **probability that each supermarket or food outlet will continue placing high-value, frequent orders**.

These models use RFM variables as predictors and return **probability scores** for each client, estimating their future business value. For instance, although both **Woolworths** and a local grocery might have similar RFM scores, a choice model could reveal that Woolworths has a **95% likelihood** of future engagement, while the local store has just **50%**. This allows for **more precise targeting**.

Python Logistics can then sort clients into **deciles**, grouping them from the **top 10% (highest probability)** to the **bottom 10%**. This enables granular strategy formulation, where each group receives tailored logistics and marketing efforts.

Decile Group	Probability	Strategy
Top 10%	> 0.90	Personalized service, priority truck slots, relationship managers
Deciles 2–4	0.70 – 0.89	Moderate engagement, scheduled follow-ups
Deciles 5–7	0.40 – 0.69	Standard logistics, retention promotions
Deciles 8–10	< 0.40	Cost-efficient service, limited priority, reactivation offers

Table 2: Choice Model-Based Decile Segmentation and Targeting Plan

Question 3: Transition Matrix and Discounted Customer Lifetime Valuation

Python Logistics can apply a **transition matrix** to understand long-term customer profitability that models how clients move between behavioural segments, such as **High Value**, **Medium Value**, and **Inactive,** over time. This approach reflects that supermarket demand patterns shift due to seasonality, competition, or management changes.

For example, a consistently active client like **McDonald's** may have a **60% chance** of staying in the High Value tier. At the same time, **Pak'nSave** might downgrade to Medium due to internal supply chain changes. Smaller outlets may churn completely after a few months. These segment shifts are tracked in a **transition matrix**, built using historical customer behaviour updated quarterly.

Once future transitions are estimated, Python Logistics can calculate **Customer Lifetime Value (CLV)** by projecting profits from each segment and applying a **discount rate** (e.g., 10%) to account for the **time value of money**. For instance, a $10,000 profit expected in 1 year is worth only $9,090 today. This ensures near-term cash flows are valued more than distant, uncertain ones.

Python logistics can compute a **risk-adjusted CLV** per client by combining transition probabilities with discounted revenue. This helps:

- **Prioritize retention** of high-value customers,
- **Optimize truck allocation** for long-term ROI,
- **Identify declining accounts** early for intervention or reallocation.

Value	High Value	Medium Value	Inactive
High Value	60%	30%	10%
Medium Value	40%	40%	20%
Inactive	0%	10%	90%

Table 3: Sample Transition Matrix for Customer Segments.

References

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