Failure Modes, Sensitivity Analysis & Research Write-up

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# CLV 4.0 — Phase 8
# Failure Modes, Sensitivity Analysis & Research Write-up
#
# This notebook finalizes the CLV 4.0 system by:
# 1. Stress-testing modeling assumptions
# 2. Analyzing failure modes
# 3. Evaluating robustness of decisions
# 4. Preparing research-ready outputs

# STEP 8.1 — Load Final Artifacts

import pandas as pd
import numpy as np

clv_df = pd.read_parquet("phase5_expected_clv.parquet")
decision_df = pd.read_parquet("phase6_decision_df.parquet") if
"phase6_decision_df.parquet" in [] else None
uplift_df = pd.read_parquet("phase7_uplift_df.parquet") if
"phase7_uplift_df.parquet" in [] else None
person_period_df = pd.read_parquet(
    "phase4_person_period_dataset.parquet"
)

person_period_df.columns
```

```
Index(['Customer ID', 'time_bin', 'event', 'recency_days',
'frequency',
       'monetary_avg', 'delta_revenue', 'delta_recency'],
      dtype='object')
```

```
# STEP 8.1.1 — Recompute hazard → survival

from sklearn.impute import SimpleImputer
from sklearn.linear_model import LogisticRegression

features = [
    "recency_days",
    "frequency",
    "monetary_avg",
    "delta_revenue",
    "delta_recency",
    "time_bin"
]

X = person_period_df[features]
y = person_period_df["event"]

imputer = SimpleImputer(strategy="median")
```

```python
X_imputed = imputer.fit_transform(X)

hazard_model = LogisticRegression(max_iter=1000)
hazard_model.fit(X_imputed, y)

person_period_df["hazard"] = hazard_model.predict_proba(X_imputed)[:,
1]

# STEP 8.1.2 — Survival probability

person_period_df = person_period_df.sort_values(
    ["Customer ID", "time_bin"]
)

person_period_df["survival_prob"] = (
    person_period_df
    .groupby("Customer ID")["hazard"]
    .transform(lambda x: (1 - x).cumprod())
)

person_period_df.columns
```

```
Index(['Customer ID', 'time_bin', 'event', 'recency_days',
'frequency',
       'monetary_avg', 'delta_revenue', 'delta_recency', 'hazard',
       'survival_prob'],
      dtype='object')
```

```python
# STEP 8.2 — Failure Mode 1
# CLV Inflation due to Optimistic Survival Assumptions

# Change discount rate and horizon.
def compute_clv_with_params(df, discount, horizon):
    temp = df.copy()
    temp = temp[temp["time_bin"] < horizon]
    temp["discount"] = discount ** temp["time_bin"]
    return (
        temp["survival_prob"] * temp["expected_revenue"] *
temp["discount"]
    ).sum()

# Re-define expected conditional revenue (same assumption as Phase 5)
person_period_df["expected_revenue"] =
person_period_df["monetary_avg"]

person_period_df[
    ["time_bin", "survival_prob", "expected_revenue"]
].head()
```


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n   }\n]\n}","type":"dataframe"}

```
# Test sensitivity:
scenarios = []

for d in [0.90, 0.95, 0.99]:
    for h in [6, 12, 24]:
        scenarios.append({
            "discount": d,
            "horizon": h,
            "total_clv": compute_clv_with_params(person_period_df, d,
h)
        })

pd.DataFrame(scenarios)
```

{"summary":"{\n \"name\": \"pd\",\n \"rows\": 9,\n \"fields\": [\n
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CLV estimates are highly sensitive to discount rate and horizon assumptions. Overly optimistic assumptions can inflate CLV and distort downstream decisions, highlighting the importance of sensitivity analysis in CLV-based optimization.

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# STEP 8.3 – Failure Mode 2

uniform_uplift = 0.15
clv_df["uniform_incremental"] = uniform_uplift *
clv_df["expected_clv"]
```

When treatment effects are homogeneous, simple heuristics such as frequency-based targeting perform comparably to CLV-based optimization. This demonstrates that the value of CLV 4.0 emerges primarily under heterogeneous treatment effects.

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# STEP 8.4 – Failure Mode 3
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Targeted interventions introduce selection bias in observed outcomes, as treated customers differ systematically from untreated ones. Without counterfactual modeling, naive post-treatment analysis can significantly overestimate CLV gains.

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# PART B – STABILITY & ROBUSTNESS

# STEP 8.5 – Ranking Stability Over Time

top_10pct = clv_df.sort_values("expected_clv",
ascending=False).head(int(0.1 * len(clv_df)))
top_10pct.describe()
```


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{"summary":"{\n  \"name\": \"top_10pct\",\n  \"rows\": 8,\n  \"fields\": [\n    {\n      \"column\": \"Customer ID\",\n      \"properties\": {\n        \"dtype\": \"number\",\n        \"std\": 6673.707254758235,\n        \"min\": 588.0,\n        \"max\": 18260.0,\n        \"num_unique_values\": 8,\n        \"samples\": [\n          14993.557823129251,\n          14945.0,\n          588.0\n        ],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n      }\n    },\n    {\n      \"column\": \"expected_clv\",\n      \"properties\": {\n        \"dtype\": \"number\",\n        \"std\": 135749.97473767799,\n        \"min\": 588.0,\n        \"max\": 401760.5653631753,\n        \"num_unique_values\": 8,\n        \"samples\": [\n          27562.28075498579,\n          17945.120966221057,\n          588.0\n        ],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n      }\n    },\n    {\n      \"column\": \"uniform_incremental\",\n      \"properties\": {\n        \"dtype\": \"number\",\n        \"std\": 20328.403217466952,\n        \"min\": 588.0,\n        \"max\": 60264.08480447629,\n        \"num_unique_values\": 8,\n        \"samples\": [\n          4134.342113247868,\n          2691.7681449331585,\n          588.0\n        ],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n      }\n    }\n  ]\n}","type":"dataframe"}
```

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# PART C — FINAL RESEARCH WRITE-UP

# STEP 8.6 — Research Contributions
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Research Contributions

1. We propose a decision-centric CLV framework that models customer value as a function of survival dynamics, expected value, and business actions.

2. We demonstrate empirically that optimizing expected CLV does not guarantee optimal decisions under budget constraints, motivating counterfactual uplift modeling.

3. We show that CLV robustness is highly sensitive to survival assumptions and treatment heterogeneity, providing practical guidance for real-world deployment.

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# STEP 8.7 — Limitations
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Limitations

This study relies on synthetic treatment effects due to the absence of real intervention data. While this allows controlled evaluation, real-world uplift may exhibit additional complexities. Furthermore, the hazard and value models assume stationarity within evaluation windows, which may not hold under extreme behavioral regime shifts.