**Delinquency Project**

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# What levers do we have?

The work presented in this document is driven by the following levers:

1. Which Orders should I cancel? (Risk)
2. How do I set up Spending Limits? (Risk)
3. How do we align marketing towards low risk Registrants/Buyers? (Marketing)
4. Enforce stricter eligibility file processes for high-risk clients (IT)

The work and deliverables should serve at least one of the above questions.

# Which Orders should I cancel?

**Learning**:

1. It is unlikely that cancelling Orders will result in a positive impact to our baseline. Order scoring may have a supplemental role in decision making.

**Developments**:

1. The development & validation of an Order scoring model that can be used to supplement the current Order vetting process (Complete).
2. Automation of Order scoring (WIP).

**Deliverables & Execution**:

1. A daily report on previous day risky Orders (Complete).
2. An Automated Order score fed into the Interceptas system (not started yet).

## How risky should an order be to justify cancelling?

Before we proceed with the question in hand, let us ask ourselves: How risky should an order be in order to cancel it? For example, if someone told us that Order A has 40% probability of charging-off in the future, would this be enough justification to cancel it? In order to answer this question, we consider the following Order components (i) Order Value (*Value*), (ii) Product Cost (*Cost*), (iii) Applied Amount (*Applied*) – the amount paid by the Buyer before charging off. If the Order is paid in full, the business benefit can be quantified as *Value – Cost*. If, on the other hand, the Order Charges off, the business makes *Applied – Cost* (which can be negative). Therefore, if we denote the probability of charging off as *p* then the expected Order benefit can be expressed as

(1-p) \* (Value – Cost) + p \* (Applied – Cost) (1)

Then the break-even probability can be expressed as (by setting the above to zero and solving for p). We know that the margin we typically operate is about 38% and therefore we can set

Cost = (1-38%) \* Value (2)

We also know that Buyers, on average pay about 45% of the Order value before charging off. Therefore, we can set

Applied = 45% \* Value (3)

If we set (1) to zero and solve for *p* we get

(1-p) \* (Value – 0.62 \* Value) = - p (0.45 \* Value – 0.62 \* Value)

or

p = 69%

So, we must be at least 69% sure that an Order will charge off in order to cancel and have a positive impact to our baseline. The implication of this is that a model must be scoring enough orders above that threshold in order to be useful for implementation.

## Towards a Scoring Model

We developed an Order Scoring model that will assign a propensity for future charge-offs. We considered various Order, Buyer & Client attributes and kept the ones with a non-negligible predictive power. The table below lists the model inputs ordered by predictive power:

|  |  |
| --- | --- |
| **Attribute** | **Information Value** |
| Salary | 0.3805 |
| Tenure | 0.3145 |
| Client Performance | 0.2111 |
| Days since Registration | 0.0825 |
| Product(s) Department | 0.0393 |
| Usergroup | 0.0361 |
| Product(s) Class | 0.0247 |
| Discount | 0.0182 |
| State | 0.0174 |
| Number of Eligibles | 0.0169 |
| Demand Value | 0.0149 |
| Shiptype | 0.0115 |
| Product(s) Subclass | 0.0073 |
| Order Month | 0.0068 |
| Order Hour | 0.005 |

The model has an AUC score of 0.745 implying a generally good discrimination capability. We also performed a series of validation steps on a hold-out (or test data set). For more information we refer to the model technical documentation.

## Is the Scoring Model useful?

In order to assess whether the model has any practical usefulness in the context of cancelling high scoring orders, we performed a series of historical simulations on a test data set. We examined the Collected Revenue vs Product Cost for Orders scoring above 50%. It turns out that the sum of Collected Revenue was 20% higher than the sum of Product Cost. This comes in agreement with the previous threshold estimate of 69%. The % of Orders ranked above 69% is very small, less than 0.5%.

Therefore, we conclude that cancelling Orders will most likely will not have any effect to our baseline.

# How do I set up Spending Limits?

**Learnings**:

1. Higher Spending Limits do not result in higher losses
2. There is no Buyer segment (with respect to Tenure & Salary) with a negative impact to our baseline. Therefore, cancelling Spending Limits is not recommended
3. Generally, charged off Registrants do not utilize their SL much differently than the rest of the Buyer population. Thus, the design of SL policies a challenging task.

**Developments**:

1. Development & Validation of a Registrant risk score (Complete).
2. Automation of the Registrant score (WIP)

**Deliverables & Execution**:

1. Partner with the Risk team towards developing data driven Spending Limit processes using Registrant risk segments (WIP).

## A Registrant Score

In order to inform the setting of Spending Limits we created a Registrant score in a similar manner to a the previously described Order score. The score is the propensity of a Registrant charging off if he/she places an order today. The Registrant score is validated in a similar manner to the Order score and takes as inputs the following parameters: (i) Salary, (ii) Tenure, (iii) Client historical performance, and (iv) Time Since Registration.

Typically, the score should increase with the Tenure and/or Salary of the Registrant. We performed some analytics on the score (using a holdout data set) and explore its relationship to losses. In the table below, we create five equally sized Segments based on the Registrant score at the time of first purchase. Then we observed the performance of each segment.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Segments** | **Count** | **Min Score** | **Max Score** | **Charge Off** | **Order Value** | **Loss** | **Loss per Order** | **SL utilization** |
| 1 | 5125 | 2% | 7% | 5% | $1,197 | $173,374 | $34 | 23% |
| 2 | 5097 | 7% | 12% | 9% | $1,159 | $369,328 | $72 | 33% |
| 3 | 5129 | 12% | 18% | 15% | $1,080 | $520,613 | $102 | 40% |
| 4 | 5147 | 18% | 27% | 21% | $878 | $587,365 | $114 | 47% |
| 5 | 5160 | 27% | 58% | 37% | $667 | $736,765 | $143 | 55% |

The above table demonstrates how the 5th Segment (high risk) results in five time more Losses than the equally sized Segment 1 (low risk).

The scope of this paper is to document the analysis of various hypotheses on the delinquency of PPC Buyers.

## A look into the high-risk segment

We take a closer look into the Spending Limit utilization of the high-risk segment. We want to compare the historical SL utilization of the Completed vs Charge Off orders. The plot below illustrates the density of the SL utilization for the two groups (the red is the Charge Off).

## 

The table below illustrates the summary statistics for the two groups.

|  |  |  |  |
| --- | --- | --- | --- |
| SL Utilization | | | |
|  | Q1 | Median | Q3 |
| Charge Off | 0.35 | 0.61 | 0.91 |
| Paid | 0.33 | 0.52 | 0.82 |

It is evident there is no vast difference between the two groups.

## Hypothesis 1: Higher Spending Limits result in higher losses

Buyer *Spending Limits* (SLs) is of the key levers for controlling the trade-off between Demand & Delinquency losses. We investigate a long-standing hypothesis of whether higher SLs result in higher losses.

### Outcome: Higher SLs do not result in higher losses.

Our analysis rejects the hypothesis. To the contrary of the hypothesis statement, data shows that Buyers with lower SLs incur higher losses. As we will see below, this observation can be explained by the fact that (i) Buyers with lower SLs typically belong to high-risk groups, i.e., low salary and low *tenure*, and (ii) Order value does not follow SLs in a linear fashion. Simply put, Buyers with lower SLs place similar value Orders as Buyers with high SLs but because they *charge-off* more frequently, they accumulate higher losses.

### Data & Methodology

We examined 69,317 *first time* orders placed by *Affiliate* Buyers between Jan 1st, 2018, and December 31st, 2018. We also calculated the SL of each Buyer at the time of the order. This was a time-consuming step as it necessitated the reverse-engineering of the SL (we do not store SL records at the time of Buyer eligibility or order placement). As a result, the calculated SL approximates the actual (and unknown) SL but we believe it is accurate enough for our analysis.

We ranked the Orders by their Buyer SLs and binned them into quartiles. The quartile summary statistics are displayed below:

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Quartile** | **Orders** | **SL (Median)** | **Salary (Median)** | **Losses** | **Tenure (Median)** | **Order Value (Median)** |
| 1 | 17330 | 1100 | 32240 | 1498975 | 25 | 648 |
| 2 | 17329 | 2175 | 34944 | 1851335 | 19 | 805 |
| 3 | 17329 | 2900 | 38316 | 1548485 | 29 | 896 |
| 4 | 17329 | 4000 | 44270 | 947099 | 91 | 924 |

Notice that, Quartile 4 contains the Orders with the higher SLs (median of $4,000). However, it results in an aggregate loss of $947,099 the lowest of all other three Quartiles.

It is interesting to note the Order value and its the relationship to the corresponding SL. Even though Quartile 4 has a median SL almost 4 times higher than Quantile 1 ($4,000 vs $1,100), the corresponding median Order value is only 30% higher ($924 vs $648).

### What is next?

The next question that comes up is whether the reduction of SLs, particularly for Quantiles 1, 2 & 3, could have prevented some of the losses. For this, we studied the SL “utilization”, that is, the ratio between Order value and SL. We want to verify whether Buyers of Quartiles 1, 2 & 3 exhaust or come close to depleting their SLs. If this is the case, then reducing SLs for certain segments could have a positive impact on the losses. The SL utilization for the four groups is summarized below:

|  |  |  |  |
| --- | --- | --- | --- |
| **Quartile** | **Q1** | **Median** | **Q3** |
| 1 | 0.35 | 0.60 | 0.87 |
| 2 | 0.21 | 0.37 | 0.57 |
| 3 | 0.17 | 0.30 | 0.49 |
| 4 | 0.13 | 0.23 | 0.39 |

As expected, Group 1 has the highest utilization of all groups. However, 50% of users are utilizing less than 60% of their SL so it is still inconclusive on whether reducing SL on any of the quartiles could result in a positive outcome. The next question is whether exists an Order segment that has been historically recorded to incur a negative impact on our baseline. This is the topic of the next section.

## Hypothesis 2: There is a Buyer segment with a negative impact on our baseline

We investigate the hypothesis that there exists a Buyer segment defined by (i) Salary, (ii) Tenure, and (iii) SL that has a negative contribution to our baseline.

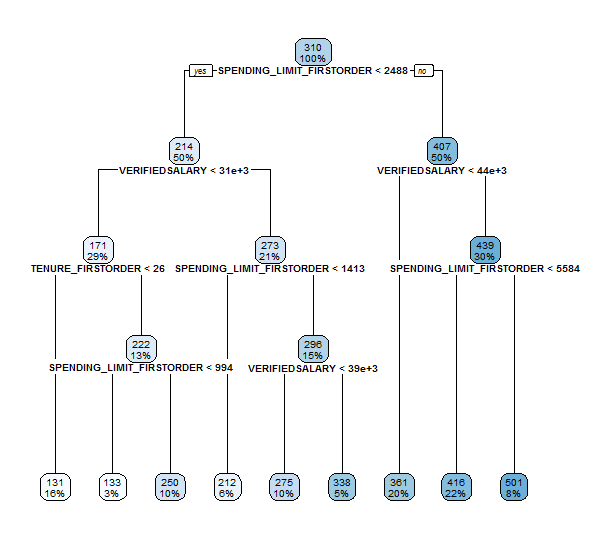
### Outcome: No such segment exists

As we will describe in the next section, we ran a Recursive Partitioning and Regression Tree algorithm to identify homogeneous groups of Orders to create a decision tree that classifies members of a population by splitting then into sub-populations base on several dichotomous independent variables.

### Data & Methodology

First, we need to define what do we mean by a “negative contribution”. First, we define three Order components: (i) *Original* (original order monetary value), (ii) *Applied* (sum of applied payments), and (iii) *Cost* (the cost associated with an order, we consider Product & Shipping Costs). We define an Order contribution as “Applied” - “Cost”. Simply put, an Order with a negative contribution is an Order where we lose money.

Working with the same set of 2018 Orders, we run a Recursive Partitioning algorithm to segment Orders into homogeneous groups based on their “contribution”. The goal is to uncover the existence of groups with a total negative contribution. Below is a graphical representation of the tree:



All the groups identified by the algorithm have a positive average contribution. Therefore, the hypothesis is rejected. The two groups with the lowest average contribution are on the left of the graph with a contribution of $131 & $133 and they account for 19% of total orders.

**What is next?**

The implication of the above hypothesis rejection is that there is no set of rules (from the ones we examined) that could identify a risky group to use for a quick win. We take a closer look at the worst-performing segment in search of additional clues that can guide our effort. The worst-performing segment is defined as follows:

**Segment A**: Spending Limit <= $2488, Salary <= $31,000, Tenure <= 26

We look at the Order Value vs SL ratio and it is:

|  |  |  |
| --- | --- | --- |
| Q1 | Median | Q3 |
| 0.3060 | 0.4840 | 0.7550 |

From the above, we see that this segment does not exhaust the available SL and therefore any initiatives for reducing SLs are not guaranteed success.

# How do we align marketing towards low risk registrants?

**Learnings**:

1. The Registrant risk score has properties that make it ideal for Marketing initiatives. The top 20% is three times more valuable (in terms of collected Net Margin) than the bottom 20%.

**Developments**:

1. Development & Validation of a Registrant risk score (Complete).
2. Registrant Segments to be used in Marketing initiatives (WIP)

**Deliverables & Execution**:

1. Partner with Marketing team on the design of initiatives towards high value Registrants. (WIP)

**A Buyer Score for Marketing**

The Buyer score presented in the previous section was designed to rank Registrants based on their propensity to charge off. Interestingly, its properties make it ideal for Marketing purposes. It suggests Registrant segments that can be used for customized marketing strategies targeting low risk Registrants.

In the table below we present additional metrics for the five Registrant segments we examined in the previous section:

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Segment** | **Count** | **Order Value** | **Collected Margin per First Order** | **Registration to First Order** | **Tenure** | **Salary** | **Demand** |
| 1 | 5125 | $1,197 | $443.00 | 17 | 143 | $49,159 | $6,133,704 |
| 2 | 5097 | $1,159 | $402.00 | 20 | 42 | $42,536 | $5,905,097 |
| 3 | 5129 | $1,080 | $355.00 | 26 | 26 | $37,274 | $5,541,424 |
| 4 | 5147 | $878 | $272.00 | 34 | 20 | $31,537 | $4,520,941 |
| 5 | 5160 | $667 | $152.00 | 32 | 15 | $25,480 | $3,440,806 |

The most interesting statistic is the “Collected Margin per First Order” which illustrates how Segment 1 (low risk) performs almost three times better than the high-risk Segment 5 ($443 vs $152).

This last observation highlights the fact that Registrant value can variate significantly, and we need to deploy advanced methods to measure and apply customized strategies on the high value Registrant segments.

## Predicting Net Margin

Inspired by the Registrant score we compile a model to predict the “Collected Net Margin”. The model uses the same predictors as the Risk Score but a different (continuous) response variable. Such a model would provide a natural Registrant segmentation. The model accepts the following inputs (i) Salary, (ii) Tenure, (iii) Client Performance, (iv) Catalogue, and (v) Time since Registration. Model validation is performed on a holdout set:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Segment** | **Count** | **Predicted** | **Actual** | **Delinquency** | **Net Margin** |
| 1 | 9370 | $224 | $243 | 33.7% | $492 |
| 2 | 9358 | $464 | $471 | 17.5% | $692 |
| 3 | 9363 | $662 | $668 | 13.9% | $946 |
| 4 | 9377 | $805 | $809 | 10.8% | $1084 |
| 5 | 9333 | $962 | $946 | 7.7% | $1177 |

The above table illustrates (i) the predictive model can accurately predict “Collected Net Margin”, and (ii) the value gap between segments: Segment 1 is 4.3 times more valuable than segment 4.

Segmenting customers based on the above prediction can serve two KPIs: (i) Delinquency, and (ii) Marketing.

A similar model can be compiled for the One-Time Buyers. The model also considers the remaining balance of the first order. The validation table is

|  |  |  |  |
| --- | --- | --- | --- |
| **Segment** | **Count** | **Predicted** | **Actual** |
| 1 | 7462 | $238 | $286 |
| 2 | 7462 | $473 | $494 |
| 3 | 7460 | $636 | $656 |
| 4 | 7461 | $785 | $786 |
| 5 | 7461 | $1041 | $1027 |

## Rolling up on a Client Level

We can easily rollup the prediction to a Client level. Top three clients

|  |  |
| --- | --- |
| **Client** | **Count** |
| LEIDOS, INC | $841 |
| ARTHUR J GALLAGHER & CO | $767 |
| INTERNATIONAL PAPER COMPANY | $750 |

And last three

|  |  |
| --- | --- |
| **Client** | **Count** |
| KOHL'S DEPARTMENT STORES | $289 |
| TYSON FOODS | $288 |
| WALGREENS PART-TIME | $285 |

## Next Steps

Currently, Marketing team uses a “time-based” segmentation for Registrants. The Registrant segmentation above is “value-based” and can present significant opportunity.

1. AB Test customized strategies on the high value segments
2. Rollup on a client level to identify high value clients for customized client-level strategies

# Enforce strict eligibility file processes for high-risk clients

**Learnings**:

1. Rolling up the Registrant risk score to a Client Level can also help us segment Clients into risk groups.

**Developments**:

1. Development & Validation of a Registrant risk score (Complete).
2. A Client list ranked by order of risk (Complete).

**Execution**:

1. Work with the IT team and identify stricter eligibility processes for high risk clients (Not started)

## Compiling a Client List

An example of a Client list is demonstrated below. Clients are ordered by their average Registrant score with the riskiest Clients on top of the list.

|  |  |  |
| --- | --- | --- |
| **Client ID** | **Client Name** | **Registrant Score** |
| 2402 | REGIS CORPORATION | 0.25 |
| 2333 | SIGNATURE HEALTHCARE | 0.21 |
| 2378 | ROSS STORES INC. | 0.21 |
| 2225 | KOHL'S DEPARTMENT STORES | 0.19 |
| 2248 | ENCOMPASS HEALTH | 0.17 |
| 2385 | TRILOGY HEALTH SERVICES, LLC | 0.16 |
| 2421 | TBC CORPORATION | 0.16 |
| 2342 | AMERICAN RED CROSS | 0.16 |
| 2486 | FUNDAMENTAL ADMINISTRATIVE SERVICES | 0.16 |
| 2149 | TYSON FOODS | 0.16 |
| 2297 | CENTURY LINK | 0.15 |
| 2376 | GOODYEAR | 0.15 |
| 2194 | WELLSTAR HEALTH SYSTEM | 0.14 |
| 2425 | C&S WHOLESALE GROCERS | 0.14 |
| 2496 | COMPASS GROUP | 0.14 |
| 2394 | SUNRISE SENIOR LIVING | 0.14 |