Credit Risk Management in OFS

A Detailed Summary of Lending through Ola Money Postpaid (OMPP)

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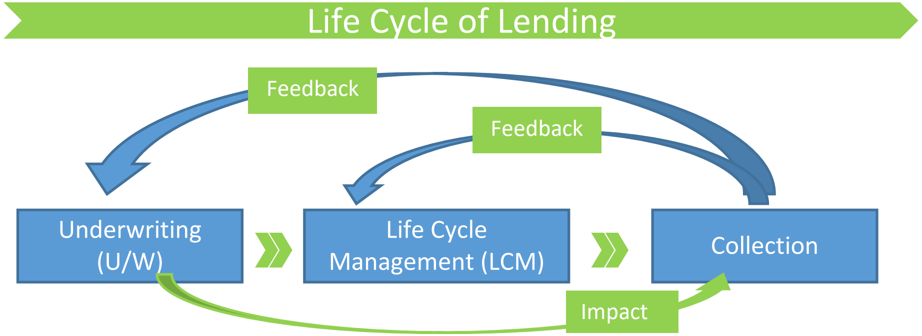
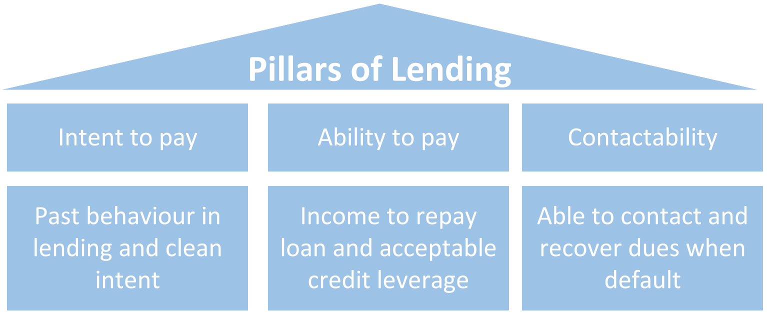
Section 1

Credit Principles

Applied to Postpaid Lending

Credit Lifecycle and pillars of lending - Application to OMPP





On OMPP

- U/W is driven primarily by loyalty, cabs need, risk proxies from Ola
- Initial Lines - 500 to 4000 in increments of 500
- Adoption rates vary for cashless (40%) vs. cash (10%) in first 1 Mon
- LCM & Line increase follows low and grow. User proves good risk first to get higher line as reward.
- Line focused on cabs need majorly for now which keeps getting updated as per usage on Ola
- Collections driven by cabs usage → subject to mobility demand and cabs supply variations

On OMPP

1. Intent to Pay factored into models used for enablement
   - Deterrent: Essential factor in Lending is less intense. Late Fee from Jan 19 added muscle
2. Ability to Pay is derived as proxy of cabs GMV
   - Bureau data being used from Jun 18 for income proxies and "off Ola" net worth
3. Contactability is phone based identity
   - Verification is contingent on cabs usage. Alt contact info sourced from bureau

Section 2

Underwriting

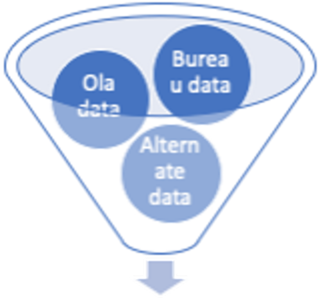
Underwriting in OMPP

WHY

- Lending is balancing risk and revenue → Quality of books to achieve this right mix is determined by underwriting
- Customer acquisition is biased usually towards high risk (credit hungry will adopt fast). Keeping off such unwanted early adopters is key to manage customer acquisition cost (CAC) as eventual losses constitute CAC
- Lack of a strong deterrent in OMPP (viz. bureau reporting, interest charges) gives little room for risk control
- Credit worthiness keep evolving in customer lifespan. U/W waits for right signals in recent past and predicts potential performance in future.
- External factors like macroeconomics and cabs business fluctuations in Ola are difficult to predict → Baked into worst case scenarios of enablement campaigns

WHAT

- OMPP enablement is completely data-driven that combines the pillars of credit risk in Ola cabs use case
- OFS uses a mix of Ola data (focus on cashless, loyalty, ride need)+ Bureau data for U/W. Alt data in exploration stage
- Underwriting strategies are constantly monitored, investigated and restructured → Catching up with new risk trends
- Line assignment manages early adopters risk (CAC) which has to get offset by returning customer's business
- Process for constant feedback loop from both LCM and Collections in place for robust strategy refinement
- Marketing cost is non-existent other than product interventions in the initial phase of campaign launch

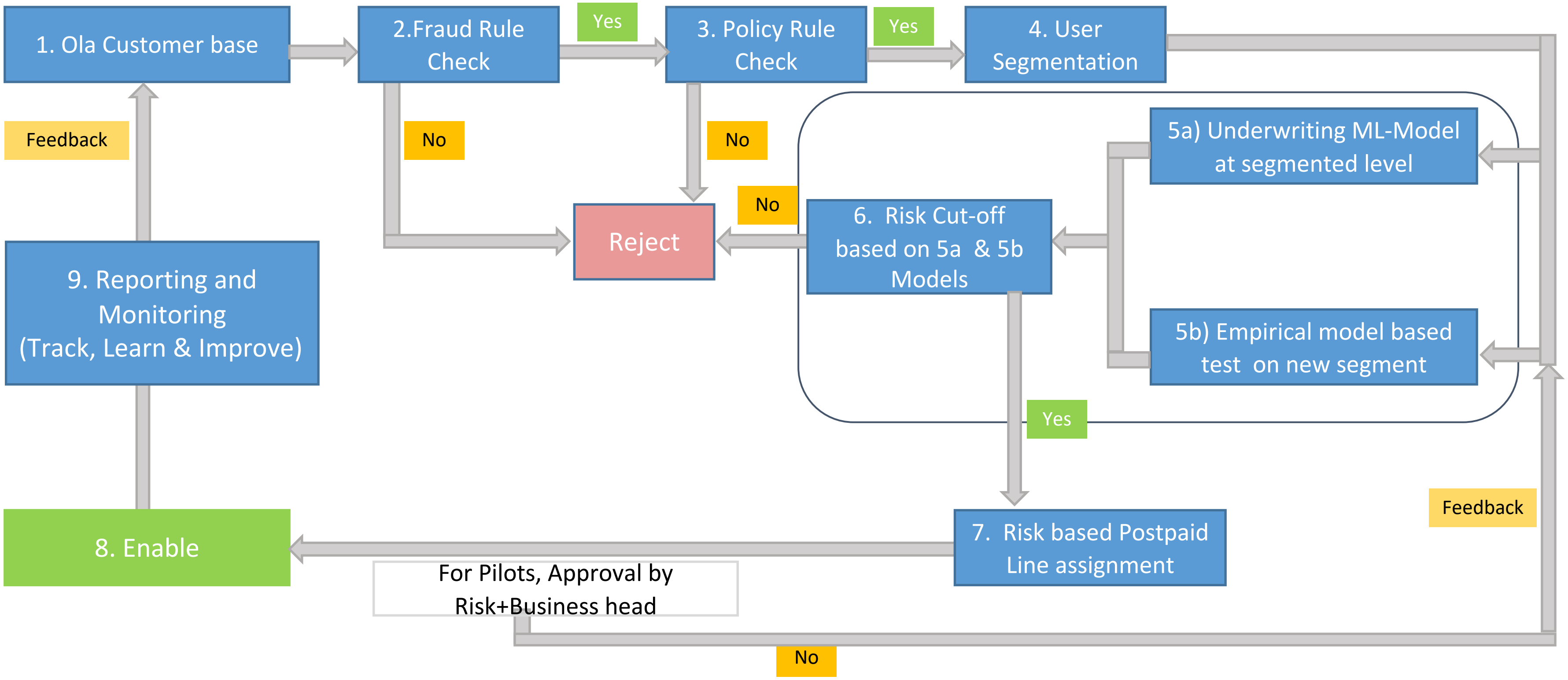


Customers' show great loyalty if credit product is offered to them at right time, also many customers prefer the lending product for convenience

Section 2.1

Process flow

Underwriting Process Flow



Each month there are multiple U/W campaigns that get launched based on experimentation (new segments) and BAU churn (proved segments) which go through the same rigour every time.

Section 2.2

Fraud and Risk Policy

Fraud policy (exclusions)

Fraud type and Definition	Example in lending	Example in Ola
1. ***First party fraud:*** An individual or group ***misrepresents*** their identity or gives false information when applying for a product or services to get more favourable deals or have no intention of repayment	Individual is aware that (s)he can not get the loan amount as per her/his need, fakes salary or applies for multiple loan (at diff lenders) to get the higher loan amount	Individual uses dual sim phone and log-in, defaults on 1 account and they start using ola new account/ log-in with 2nd account
2.* ***Second party fraud:*** An individual ***knowingly*** gives their identity/PII to ***another individual*** to commit fraud	Individual uses the credit card >> throws the credit card >> informs the lender that the spend on card is not done by the user, someone has taken over the account	Individual uses the Ola services and says that (s)he had paid in cash, so, will not return the cashless (CC/DC/OMPP etc.) dues.
3. ***Third party fraud:*** An individual creates or ***uses another person's identity to takeover*** the account	Hackers mimic PIIs of customers who can get good credit lines and apply for loans.	Drivers ask for A/C log-in from customers and take-over the account

Note: 2.* Identifying 2nd party and 3rd party fraud is really difficult. Generally, lenders/customers either toggle between "legal proceedings" or "customers experience" (ex: Amex write-offs the amount, or account is reinstated back to the customer based on minimum post mortem of fraud")

Fraud policy applied on OMPP

First party fraud (misrepresent):

- To avoid 1st party fraud, customers with dual logins (using device fingerprinting), are not being offered Ola postpaid.
    - Rule is more severe than cabs fingerprinting as the use cases and impact are disproportionate b/w cabs and OMPP
- Risk performance of such customers, shown in slide 13.

Second party fraud (PII given):

- To avoid 2nd party fraud, customers with recent time disputes on cabs platform are avoided.
- Push notification for all rides in 1st cycle that create awareness about cash paid to driver for OMPP (cashless) rides

Third party fraud (hacked PII):

- New device login OTP made 6 digit (ride 4 digit) to minimize intentional account takeover attempts by driver

Risk Policy overview

Why is it needed?

- Reduce Loss
- Reduce cost of acquisition
- Reduce ops cost
- Regulatory requirements
- Maintain homogeneity for better decisioning

Example in lending

Reject if

- Particular geography, due to high operation cost or collection cost (outskirts of metro viz. howrah)
- Income < 5 lakhs.per.annum
- Particular professions (ex: lawyers, gym owners)
- Bureau red flags: Disputes, write-off, bankruptcy
- Bureau score (ex: CIBIL/Experian score < 710), risky loans (Ex: gold loans, Krishi loans)
- Age<25

Example in Ola

Reject if

- If customer is frequenting educational institutes (potential student who can discard phone identity easily)
- Fingerprinting that detects dual login on 2 different numbers
- Users outside Top 7 cities getting high limits (field ops for collections take time to be live there)
- Customer with disputes on Ola might prompt intentional default
- Previously due on other payment instruments (CC/DC/UPI)
- Blocked by OM due to suspicious activity on wallet

Risk Policy in OMPP

Following are the controls used as policy exclusions:

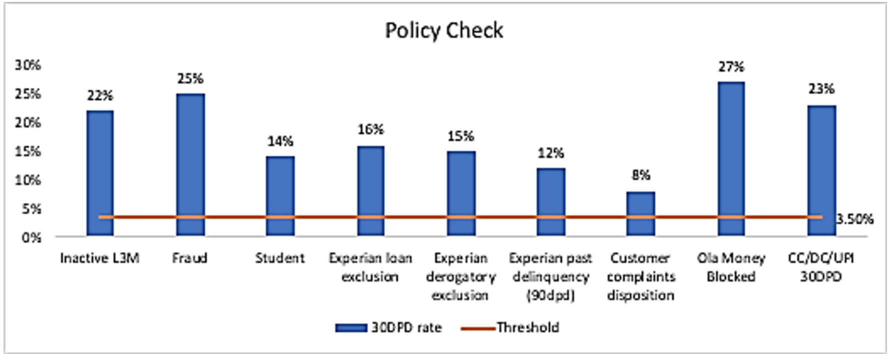
- Inactive in L3m - Low or No need for mobility solutions from Ola
- Student - Data driven student indicator that minimizes exposure to people with high tendency to skip payments
- Bureau exclusion - External bureau data driven risky profiles of people taking loans with high defaults: gold, MFI, commercial
- Experian derogatory info exclusion - suit filed, wilful default, written-off, etc
- Experian past delinquency history - 90 dpd in last 12 m
- Corporate users - potential to skip or delay payments due to nature of business using cabs for official purpose
- Customer complaints - recent fall off with cabs and ola in general; unhealthy brand perception
- Blacklist signals from internal payments - om blocked; CC/DC/UPI defaults in L6M (30 DPD+)

Impact of policy exclusions:

- Policy exclusions are 4 times higher risk than portfolio avg. risk

- Policy exclusions saves huge risk on a focused small population
    - Population getting excluded ~ 10%
    - 30 dpd risk ~ 13% for policy exclusions vs.~ 3.3% for portfolio overall

- Bureau information enhances policy exclusions further



Section 2.3

Segmentation

Segmentation

Why is it needed?

- Customer segmentations are done so that specific needs of customers can be reached in targeted manner and also Business priority can be made accordingly. Mostly 2 types of approach are used:
- ***Revenue driven:*** Revenue driven approach are used to create different strategy for different segment (Ex: CC repayment has high MDR so, can be dealt differently)
- ***Data driven approach:*** It's mostly done based on different behaviour across segment, data availability for predicting customers' behaviour

Example in lending

- Channel of acquisition driven, different acquiring channel have different activation rate and similarly different risk level
- Age/profession/income driven
- Past behaviour driven, for ex. if customer has shown loyal behaviour in some other product offered by the institutions etc.
- Geography driven

Segmentation in Ola

- Ola book segmentation is majorly based on customers' behaviour on Ola cabs, Geography and performance of customers on other lending products (data from credit bureau (Experian))

OMPP Segmentation

Segmentation is about creating intra homogeneous persona (risk) pools and inter heterogeneous risk pools.

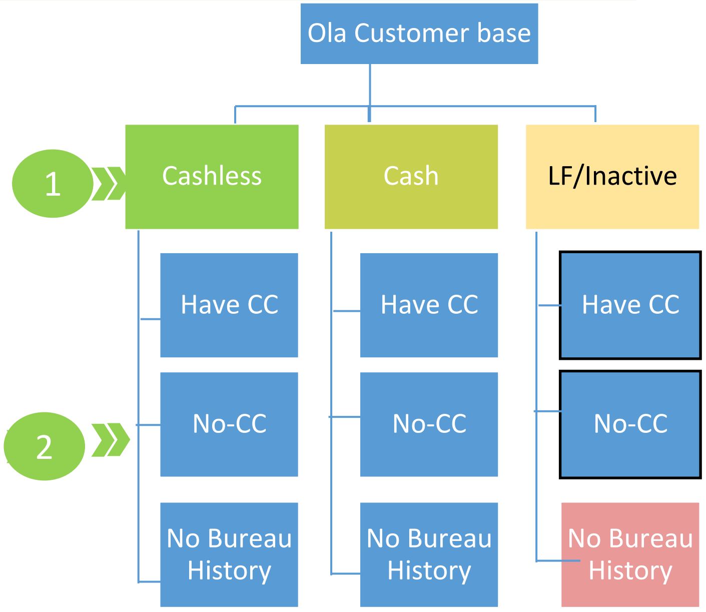
- Leads to increase in accuracy of prediction
- Aids in better control of each populations due to similarity of customers within that groups

__Level 1 segmentation__

- First level is demarcation of utility from OMPP: Those who are regular on Ola Cabs and who are not.
- Regulars are further divided into Cash and Cashless since OMPP has a better USP for one over the other.
- Final segments: a) Regular user (UHF,HF,MF) Cashless, b) Regular user cash and c) Irregular user (LF/Inactive)
- Segmentation provides risk ranking as well as adoption similarities

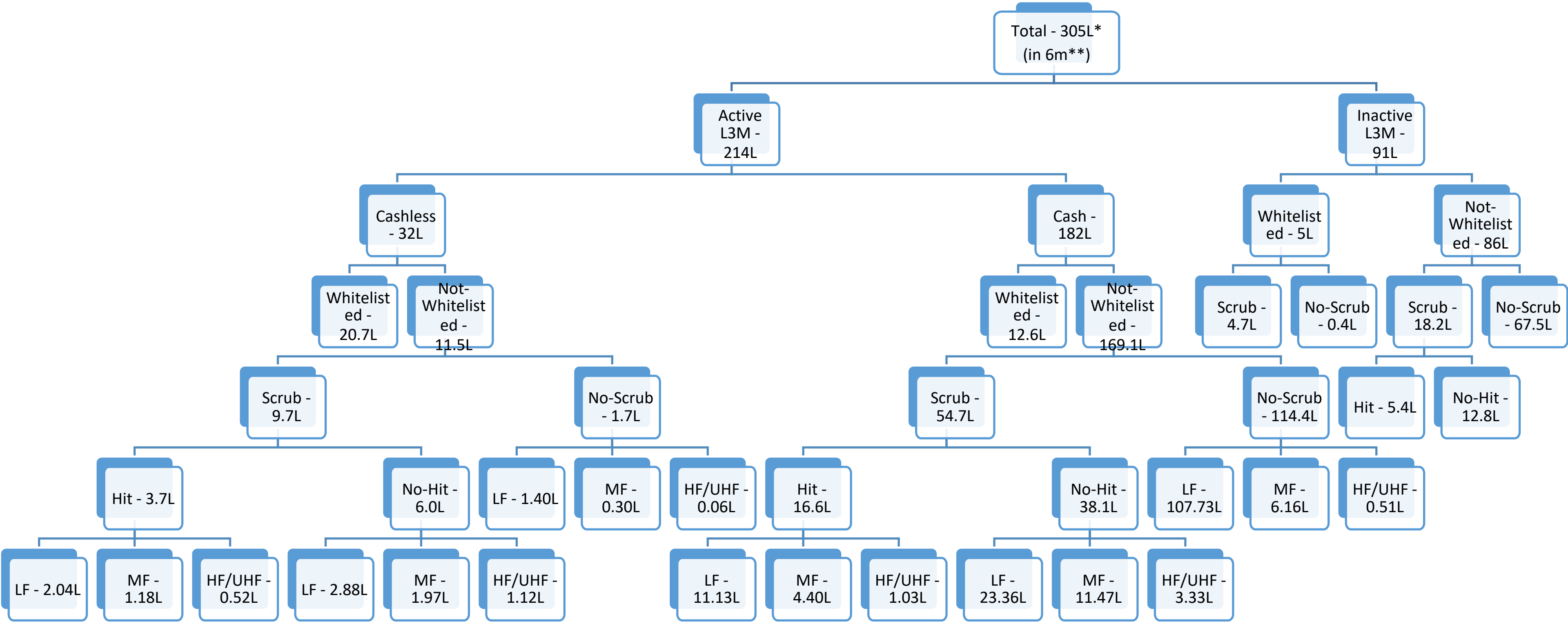
__Level 2 segmentation__

- OMPP being a revolving credit (digital CC) users with exp in using credit cards will be natural targets
- “Have CC” are better risk due to lenders’ due diligence prior to issuing cards
- “No-CC” are bureau hits but without a card. They are basically those who don’t want traditional credit cards or those who want but did not get it yet
- “No-CC” are much better risk than those not found with bureau history
- Inactive/LF evaluated on “Off Ola” features hence no-hits are excluded



With increase in OMPP base, next level of segmentations are planned based on customers’ persona, spend behaviour across different merchants, push/pull factors (right now all are push>> OMPP is reaching out to customers)

Segmentation in OMPP Underwriting



* L is lac(s); L3M is last 3 month(s)

Scrub: Bureau pull attempt made; ***No- Scrub:*** Bureau data pull attempt was not made

Hit: Bureau pull attempt returns positive match; ***No-Hit:*** Bureau pull attempt is negative

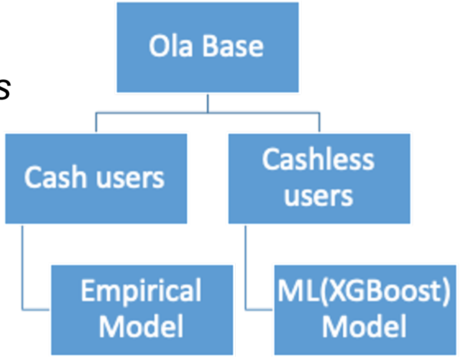
Section 2.4

Credit Risk Modeling

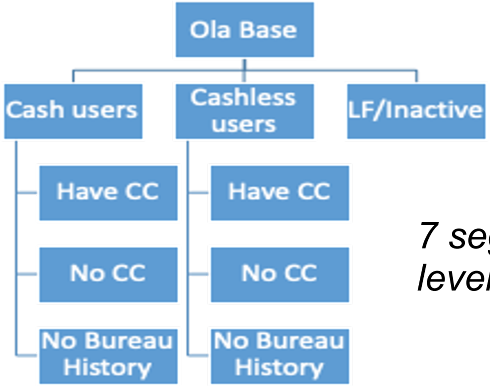
OMPP UW Modeling Transition

Early 2018

2 segment level models



Late 2018 - 2019



7 segment level models

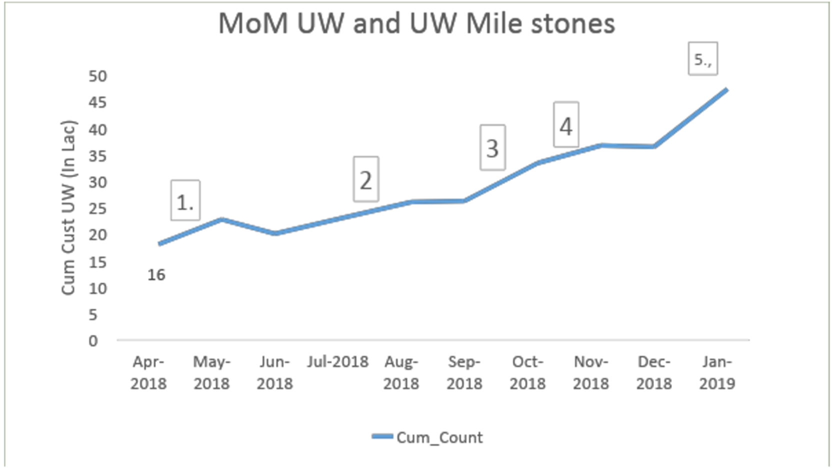
UW Strategy post Bureau Data Availability (Late 2018)

		UW Risk bucket				
		Very Low	Low	Medium	High	Very High
Experian Risk Bucket	Low					
	Medium					
	High					
	No-hit					

Journey of Cashless Model >> 2 ML models in place (5 more models under dev)

Evolution of Underwriting models

Stage 1: Business Expertise/Hypothesis based U/W » Stage 2: Preliminary model » Stage 3: Machine Learning (ML) Models



Each step is required, so that performance can be observed at controlled volume and credit risk level

Journey of Ola UW modeling - Chronological Order

1. Stage 3 model for cashless is built
2. Cashless U/W policy enhancement with bureau
3. Stage 1 U/W for Cash Bureau Hits (w and w/o CC)
4. Stage 2 model for Cash Bureau Hits (w and w/o CC)
5. Stage 3 models for cashless at segment level (Bureau Hits w, w/o CC, No Hits) using enhanced Machine Learning Algos

   Stage 3 models for cash (Bureau Hits w, w/o CC, No Hits)

   Stage 1 for LF/Inactive

Journey of Cash Models >> Expertise based Pilot model (CC Seg)

Based on the framework explained below, 5% customers are being underwritten from each segment (i.e. alpha, beta etc.), and their performance is closely observed.

Behaviour Segment		Global Segment					
		High	Medium	Low	Very_Low	No_tag	Not_known
Local Segment	HIGH	Alpha	Beta	Theta	Zeta		
	MEDIUM	Beta	Gamma	Delta	Zeta		
	LOW	Theta	Delta	Delta	Zeta		
	VERY LOW	Zeta	Zeta	Zeta	Zeta		
	Not-Known						

Global Segment		CC Tag segment					
		High	Medium	Low	Very_Low	No_tag	Not_known
Affluent Score Segment	HIGH	H	H	M			
	MEDIUM	H	M	L			
	LOW	M	L	L			
	VERY LOW						
	Not-Known						

Local segment		Mobility Tag segment					
		High	Medium	Low	Very_Low	No_tag	Not_known
SOW Segment	HIGH	H	H	H			
	MEDIUM	M	M	M			
	LOW	M	L	L			
	VERY LOW						
	Not-known						

CC Tag Segment:
- High: CC_Mnth_Spend >30k & CC_MOB > 1Y
- Medium: CC_Mnth_Spend >10k & CC_MOB > 6M
- Low: CC_Mnth_Spend >2k & CC_MOB > 3M
- Very Low: Rest

Affluent Score Segment:
- High: Score>=22 (top 10% of ola base)
- Medium: Score>=16 (next 10% of ola base)
- Low: Score>=9 (50%-80% of ola base)
- Very Low: Rest

Loyalty (Max L3M ride*3/Sum L3M ride):
- High : >=70%
- Medium : 70%>x>=55%
- Low : 55%>x>=35%
- Very Low : <35%

Mobility (#L3M Rides):
- High : >=11
- Medium: >=6 and <11
- Low : 3<=x<6
- Very Low : <3

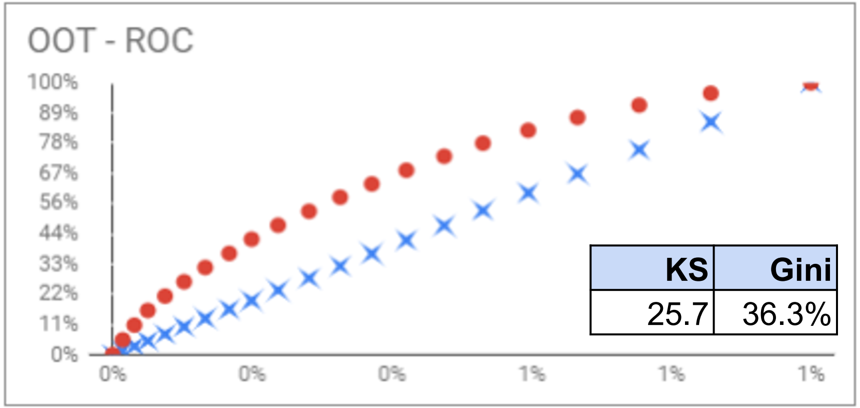
Journey of Ola Cash Model>> Stage 2 Model (Cash - CC Seg)

- Based on performance observed from enablement (based on Business expertise), initial ML model is being developed. This model rank orders on broad buckets. It has been built on very small sample (owing to low activation of Cash customers in the start). The model was mostly built on Credit Bureau data.
- Model will be able to segregate risk but not able to beat industry benchmark by high margin (GINI benchmark for UW in emerging companies/stable banks, b/w 25-30)

__Objective of Underwriting model__ is to predict if the customer will/will not be paying back OMPP bill in next 30 days

__Key features in the model:__

- *Month since 1st lending product*
- *Maximum days past due in last 6 months*
- *Age of customer (in yr)*
- *Risky loan*
- *No of time 30 days past due in past 12 months*
- *Avg. Utilization of credit card (Bal in 6 m/Line in 6 m)*



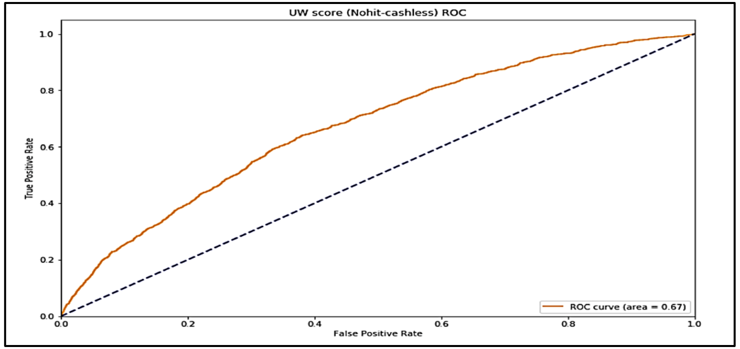
Since performance of more than 10K customers is observed. A new ML model is being developed, using Bureau data and Ola data. By end of Feb'19 Model will be mature models

Cashless mature models performance Stage 3 redevelop

Usual Top Features in cashless models	
Cash penetration	pg_amount_o_l3m
Age on Ola	Airport ride GMV spent
Zone score	OM gmv spent
OM transactions	Percentage of non-peak hour rides
True demand vs Ride demand	Ride score
Loyalty	Cashless ATS
Cash Extraction	Category - Auto, Micro, Non-share

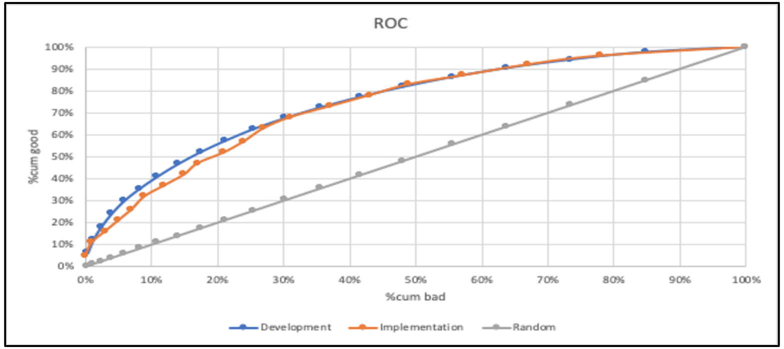
Gini chart of Cashless no hit - Feb 2019

	Gini	KS
Model Metrics	0.34	24



Gini chart of overall Cashless - May 2018

	Gini	KS
Model Metrics	0.4	31



Section 2.5

Line assignment

Initial Credit Line (ICL) strategy

Fundamentals of line assignment

Function of 3 major dimensions.

1. Risk (Using UW models rule)
2. Ability to pay (Income/Salary)
3. Organisation's risk appetite
   - Revenue growth targets
   - Loss threshold targets

Intent to Pay	Ability to Pay	Line
Low	Low	Block Line
	Medium	
	High**	Low Line
Medium	Low	Block Line
	Medium	Medium Line
	High	Medium
High	Low**	Low Line
	Medium	Medium Line
	High	High Line

OMPP broad level strategy:

1. Cross tab between the 2 pillars of credit lending are the bedrock of line magnitude in U/W
2. Within the eligible cells of the cross tab, net revenue and long term value play a role on exact amount of line assigned
3. Every cell comes with a cap on limit that restricts over exposure at such an early stage (adoption) of a customer
4. Presence of collection ops also in taken into consideration for max credit lines for eg. field ops feasibility in T7

**Note: Override of BAU strategy is done majorly in 2 case, if customers' income is too high or customers' risk is too low

Underwriting Line assignment - Process

- Ola line assignment is function of credit risk, spend behaviour on Ola, portfolio segment
    - Different risk behaviour >> less predictive power >> conservative line
- Line assignment needs Model cap (or risk guard rails), this is done to control the exposure at different risk level

The Suggested Structure is for Top-7 Cities		
Segment Name	**With CC**	Line = [Min (Guardrails, Max{ Least integer in '500 (Multipliers * 15 day GMV), Floor of the Column }]
Product Min Line	500	
Product Max ICL	4,000	

Multiplier (Avg. Spend in 15 days)

Bur-Score	MF	HF-UHF
[860, +)	1.1	2
[810-860)	1.1	1.75
[760-810)	1	1.5
[710-760)	0.9	1.1
[690-710)	0.75	0.9
[660-690)	0.5	0.5

	Model Cap (Or Guardrails)						
	Bureau Score (Experian)						
Ola Bureau Score	(860, +)	(810-860]	(760-810]	(710-760]	(690-710]	(660-690]	(-, 660]
1	4000	3500	2500	1500	1000	Outside Ola Risk Appetite	Outside Ola Risk Appetite
2	4000	3500	2500	1000	500		
3	3500	3000	2000	1000	500		
4	3000	2500	1500	500	Outside Ola risk appetite		
5	3000	2000	1500	500			
6	2500	2000	1000	Outside Ola risk appetite			
7	2000	1500	1000				
8	1500	1000	500				
9	Outside Ola Risk Appetite						
10	Outside Ola Risk Appetite						
Floor of the Column	1000	1000	500	500	500	500	

Section 2.6

Reporting and Monitoring

U/W measurement framework

- U/W is tracked at campaign level - every campaign followed till its decommissioned on app since there is no expiry. Yet to evaluate expiry of 3-6 months in future.
- Measurement focuses on
    - Early risk indicators (7DPD instead of waiting till 30 DPD) and
    - Fastest signals (1st 3 weeks of adoption for stability and volumes) that can be relied upon
- Early indicators are closely monitored by Underwriting and Leadership team (Specially in case of new tests).
- Tracking at early level (specially for hypothesis based underwriting) shows initial risk readings (callout 2) as huge. Quick actions taken on enabled but not accepted by de-whitelisting the remaining base
- All other segments have performed better (callout 1) where first 3 weeks of adopted customers show initial risk measured by 7 DPD) are within the threshold of 40%

1

2

Campaign Description	Campaign Tag	Campaign Live Date	Enabled Users	Acceptance %	Accepted Users	% Users Accepted in 3 weeks	Users Accepted in 3 weeks	Users taken first ride in 3 weeks	Users evaluated for bad rate	Cut-off 7+DPD rate	7+DPD rate (1-2 cycle)			Upto week 3 (7 dpd) > 40%
											Upto Week 1	Upto Week 2	Upto Week 3	
AgePilot_CASH_S21_age_36to40	UND_2018_OCT_16	18-Oct	2,453	20.10%	493	5.58%	137	79	79	40%	19.94%	30.28%	29.24%	0
CC_scorecardPilot_CASH_score_0to6p	UND_2018_OCT_17	20-Oct	45,000	18.21%	8,195	4.51%	2,030	1,378	1,371	40%	58.70%	53.52%	52.38%	1
CC_scorecardPilot_CASH_score_6to10	UND_2018_OCT_18	20-Oct	15,000	17.68%	2,652	4.27%	641	361	357	40%	64.69%	60.13%	59.10%	1
XGB_lessthan_6perc	UND_2018_OCT_19	23-Oct	28,414	41.98%	11,929	21.31%	6,054	3,271	3,263	40%	30.03%	28.79%	29.05%	0
XGB_dualscore_S11_existingBureau	UND_2018_OCT_20	23-Oct	28,378	39.87%	11,315	19.61%	5,566	3,021	3,018	40%	24.46%	24.66%	25.97%	0
XGB_dualscore_S12_existingBureau	UND_2018_OCT_21	23-Oct	7,801	41.70%	3,253	21.27%	1,659	950	949	40%	36.85%	38.17%	37.37%	0
XGB_dualscore_S21_existingBureau	UND_2018_OCT_22	23-Oct	15,023	45.07%	6,771	22.19%	3,333	1,873	1,871	40%	29.38%	28.57%	30.61%	0
XGB_dualscore_S22_existingBureau	UND_2018_OCT_23	23-Oct	1,807	50.91%	920	26.84%	485	293	293	40%	42.06%	37.58%	36.92%	0
CASH_ExpertScore_S11	UND_2018_OCT_24	26-Oct	49,564	16.97%	8,413	4.09%	2,028	1,222	1,212	40%	30.30%	27.01%	30.08%	0

UW measurement framework (Contd.)

- Second set of reports monitors campaigns after the initial sign off. This is done to account for macro factors in economy or within cabs platform.
- This report tracks the health by each cycle cohort and ensures that returning customer (completed cycles >2) when given 30 days to pay have a desired curing rate.
- The learning of such go-ahead campaigns both good risk as well as bad -risk are taken into consideration in the next gen model development process.

30 days past due as bad rate

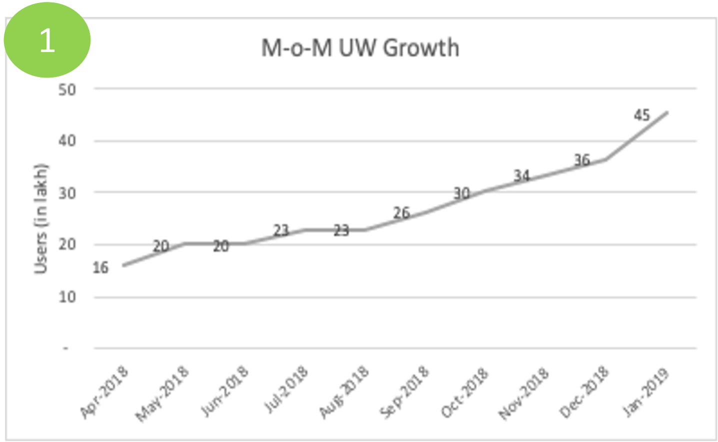
								Bad Rate %				Total Users			Total GMV		
							Cycle	1	2	3	Total	1	2	3	1	2	3
Enabled	Acceptanc	Accepted	FR rate	First Ride	Model Name	Cmpg Live Date	Campaign										
21,736	46.52%	10,112	73.71%	7,454	XGB_lessthan_6perc_S11	19-Jul	UND_2018_JUL_01	3.70%	3.10%	2.01%	2.36%	5,967	3,816	2,496	1,772,589	1,220,501	844,649
24,778	45.10%	11,176	76.21%	8,517	XGB_lessthan_6perc_S12	19-Jul	UND_2018_JUL_02	5.23%	3.87%	4.56%	3.43%	6,815	4,470	2,973	1,999,016	1,427,298	993,526
17,100	50.32%	8,604	76.87%	6,614	XGB_lessthan_6perc_S21	19-Jul	UND_2018_JUL_03	4.79%	3.96%	3.59%	3.43%	5,416	3,539	2,348	1,658,602	1,167,455	829,071
20,483	48.74%	9,983	78.24%	7,811	XGB_lessthan_6perc_S22	19-Jul	UND_2018_JUL_04	6.64%	5.42%	3.46%	4.07%	6,345	4,256	2,878	1,852,749	1,358,867	974,098
26,236	46.67%	12,244	77.11%	9,441	XGB_lessthan_6perc_NTC_noHit	19-Jul	UND_2018_JUL_05	6.33%	5.06%	4.20%	4.18%	7,727	5,060	3,318	2,323,633	1,620,021	1,128,661
44,939	43.64%	19,611	78.34%	15,363	XGB_dualscore_S11	24-Jul	UND_2018_JUL_06	5.30%	3.48%	2.98%	3.12%	12,307	8,078	5,370	3,803,830	2,652,462	1,879,062
69,893	45.26%	31,636	80.69%	25,527	XGB_dualscore_S12	24-Jul	UND_2018_JUL_07	7.73%	5.13%	4.72%	4.66%	20,704	14,038	9,603	6,108,473	4,533,299	3,305,360
12,971	47.45%	6,155	79.51%	4,894	XGB_dualscore_S21	24-Jul	UND_2018_JUL_08	5.24%	4.37%	3.11%	3.33%	3,969	2,702	1,831	1,217,326	891,092	652,140
20,435	47.66%	9,739	80.63%	7,853	XGB_dualscore_S22	24-Jul	UND_2018_JUL_09	7.27%	4.93%	4.84%	4.53%	6,448	4,408	3,023	1,889,994	1,415,165	1,042,913
6,647	46.05%	3,061	78.96%	2,417	XGB_pilot1_NTC_noHit	24-Jul	UND_2018_JUL_10	8.77%	5.45%	3.45%	4.79%	1,998	1,307	895	606,203	425,344	304,242
4,786	47.07%	2,253	81.89%	1,845	XGB_pilot2_NTC_noHit	24-Jul	UND_2018_JUL_11	9.09%	7.46%	4.81%	4.96%	1,515	1,060	727	457,798	347,999	254,263
7,860	40.93%	3,217	80.70%	2,596	XGB_pilot_highexpscore_S11	24-Jul	UND_2018_JUL_12	7.89%	4.07%	4.78%	4.90%	2,097	1,440	990	650,776	475,235	352,046
4,917	24.55%	1,207	84.42%	1,019	CASH_pilot_global_local_nonKYC_S11	5-Sep	UND_2018_SEP_01	10.82%	5.64%	2.11%	5.36%	640	403	266	438,942	317,914	229,465
1,016	19.00%	193	83.94%	162	CASH_pilot_global_local_nonKYC_S12	5-Sep	UND_2018_SEP_02	26.47%	13.12%	21.96%	18.30%	94	52	28	56,154	31,866	20,808

Section 2.7

Current Performance

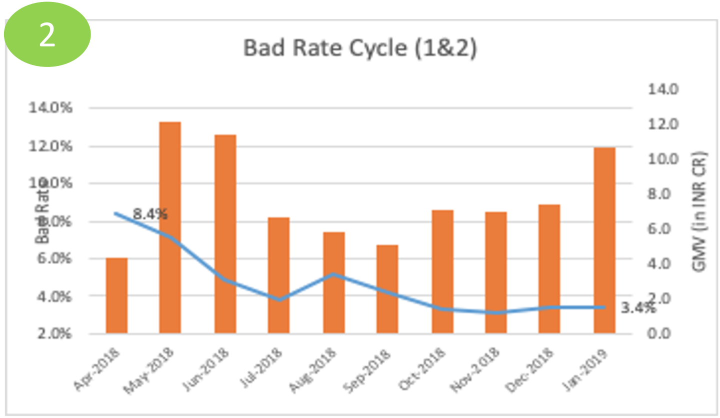
OMPP Portfolio Current State

MoM number of users whitelisted for OMPP have increased (from 16L in April'18 to 45L till date)



GMV contribution by new customers, is consistently growing over time. Spike in May and June'18 is due to New cashless ML model development in May.

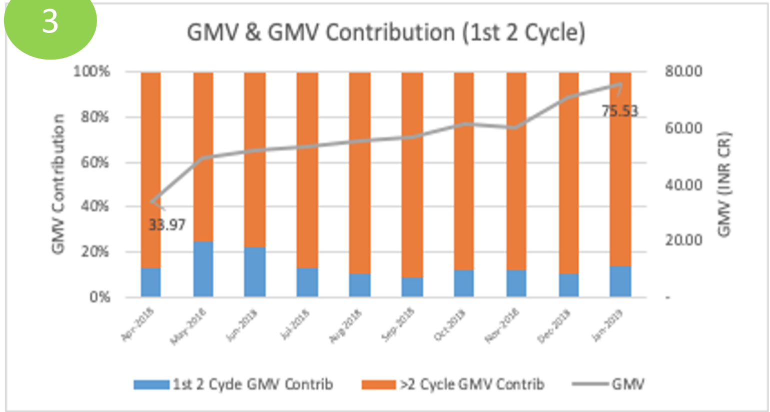
30DPD bad rate has gone done over the period. It has been consistent in the recent months (Oct-Jan'18), to maintain the growth.



OMPP Portfolio Current State (Contd.

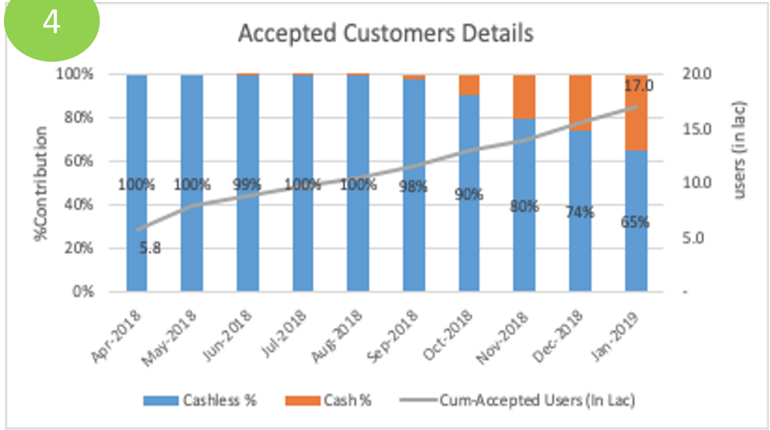
Portfolio mix of new customers (cycle 1&2) and old customers (cycle 3+) continue to remain constant, helping us keeping overall portfolio risk under control

3



Adoption of cash customers is increasing overtime consistently. Conversion of Cash base to cashlees is done in controlled manner, so that risk of overall book can be made consistent

4



Section 3

Life Cycle Management (LCM)

Life Cycle Management (Overview from OMPP standpoint)

WHY

Line increase is required to increase spend and enhance customer experience by meeting their mobility needs through OMPP (one bill for all rides)

WHEN

Limit increase is typically carried out when customer's OMPP utilization exceeds 50%. The idea is to minimize limit exhaustion

HOW

By balancing the spend or need with the intent to pay and ability to pay

LIMIT INCREASE MAGNIFIES GOOD GMV AND KEEPS PORTFOLIO BAD RATE IN CONTROL!!

- OMPP Line increase framework uses "Low and Grow" as its bedrock.
- Line increase has to be build after measuring the worthiness rather than in sudden jumps of limit. At the same time exhaustion due to spike in temporary need has to be addressed.
    - Dynamic authorisation is the ideal solution but increasing limit on a timely basis will arrest attrition.
- As and when the customer builds their profile on Ola (behavior), the account is evaluated for credit worthiness
    - Bureau data and ompp repayment data using in-house customer behavior model.
- Exhaustion at portfolio level, Avg limit of portfolio, extraction, proportion of population getting limit increase are key metrics

Strategy for different OMPP segments

Segments	Active	Inactive	Enabled not accepted
Strategy	Exposure management – increasing exposure with better credit quality customers and reducing exposure with high risk customers	Activate customers – incentivizing customers to use their line of credit again	Activate customers – incentivizing customers to use OMPP
Treatment	• Credit line increase • Credit line decrease • Dewhitelisting	• Customers inactive for longer period • Credit line increase selectively	Credit Limit update
Credit Policy consideration	• Internal behavior model score of a customer • Customers' capability to repay • Need/Utilization of customer • External information including credit seeking behavior, bankruptcy information etc.	• Customers' capability to repay • External information including credit seeking behavior, bankruptcy information etc.	• Customers' capability to repay • External information including wallet share, credit seeking behavior, bankruptcy information etc.

Section 3.1

Process Flow

OMPP Credit Limit Increase (CLI) framework:

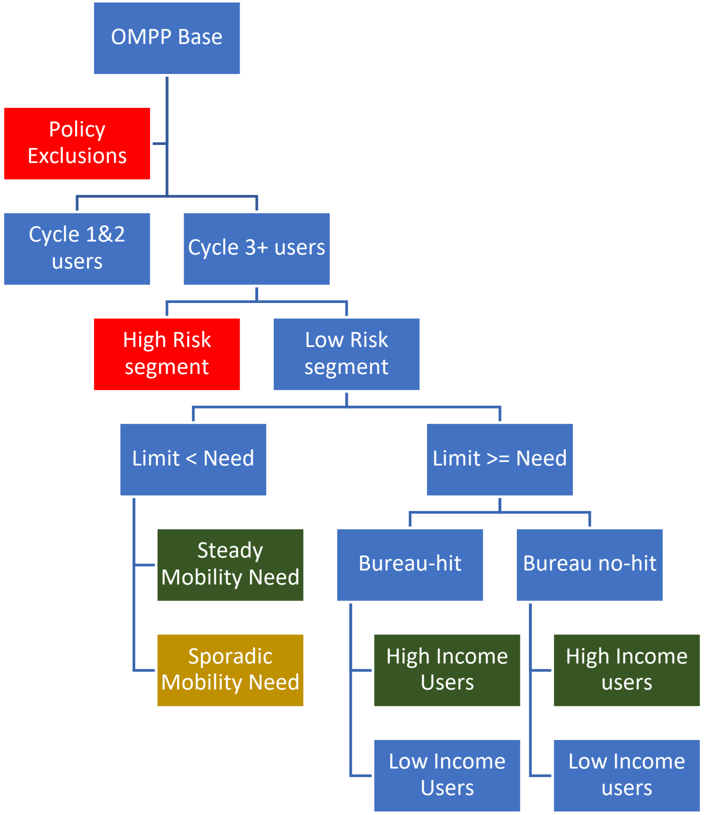
- All users failing to qualify through policy checks are excluded

- Cycle 1 & 2 users are usually not considered for limit increase, unless they are facing limit exhaustion

- For Cycle 3+ users, high risk segments are not considered for limit increase, some of which are Customers:
  - With low activity (less number of cycles in last 3 mths) have high risk
  - With repetitive delinquency (DPD) behavior in past have high risk

- For remaining cycle 3+ users considered as eligible for CLI basis:
  - If need on cabs > limit then these have need for higher limit, of which:
    - Users with regular need of cabs → significantly higher limit
    - Users with sporadic need of cabs → only to the extent of their need
  - If need on cabs < limit then reward high income users as limits should be sufficient for their sudden cab/external merchant need. High income segments are:
    - (Credit card limit >=2L or home loan>=20L or auto loan>=10L) + Score >810
    - >50% of rides with prime cabs or >3 airport/os/rental rides in last 3 month

- Low and grow strategy:
  - Users are moved from lower limit to higher limit in stages
  - Users from ROI are capped to 5k limit and from T7 are capped at 10K limit
  - For Full KYC users, limit may go up and beyond 10K



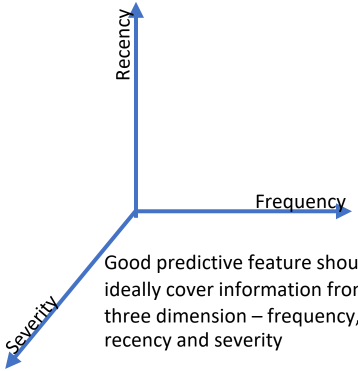
Section 3.2

Risk Policy

Predictive Features used in CLI Strategy and Modeling

OLA Delinquency features	*Bureau features*	*OMPP Utilization features*	*OLA Mobility features*	*High income proxy features*
Number of times delinquent	Bureau Score	Number of times limit exhausted	Regular versus sporadic need of Ola Cab	prime/airport/rental/os rides
Days or Cycles since delinquent	Credit Card User	Ratio of limit spent to OMPP limit	Monthly Spend on Ola	High limit on credit card, mortgage or auto loan
Delinquent amount	Delinquent behavior on bureau		Share of wallet on Ola	No personal cash loan

- Ola Delinquency features: Recency, Frequency, Severity
    - Users with repetitive delinquency (days past due) behavior in past have high risk
    - Users who have shown one incident of risk (DPD) long time back but good behavior in recent times have low risk
- Bureau features:
    - Users with Experian score <710 are considered risky for any credit product
    - Users with credit card on bureau and clean history are credit-worthy
- OMPP utilization features:
    - High continuous utilization on OMPP signals OMPP is the most preferred payment method for these users
    - Users exhausting their OMPP limits signals need for higher limit
- Ola Mobility features:
    - Regular user of Ola month over month have high mobility need and is more likely to pay on time
    - High monthly spend on Ola again shows high mobility need and hence, is more likely to pay on time
    - High Share of wallet means user is loyal to Ola and hence, will not defer payment
- Income proxy features:
    - Users with high % usage of airport/prime/rental/os rides are usually high income users and have high ability to pay
    - Users with high limit on credit card/mortgage/auto loans are high income users and hence, have high ability to pay



Good predictive feature should ideally cover information from al three dimension – frequency, recency and severity

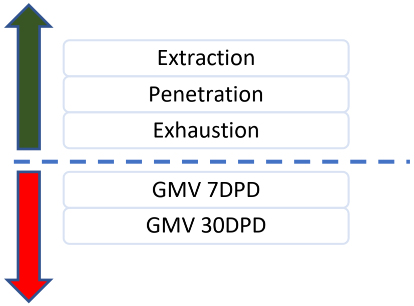
Section 3.3

Reporting and Monitoring

CLI reports

Each CLI campaign is monitored closely for any adverse results on following metrics:

- % 7DPD GMV
- % 30DPD GMV
- OMPP Extraction (OMPP GMV/ Cabs GMV) is expected to increase after limit change
- OMPP Penetration (OMPP rides/Cabs rides) is expected to increase after limit change
- OMPP exhaustion (insufficient limit) is expected to continuously reduce



Campaign monitoring metric

HEALTH STATUS

Campaign	Campaign Description	Date Rolled Out	Rolled Out	Successfully Given CLI	Cabs Active	% Cabs Active	OMPP Active	% OMPP Active
LCM_2018_Nov_01	Exhaustion	7th Nov	11,263	9,825	9,402	96%	9,085	97%
LCM_2018_Nov_02	BAU based on 2nd Highest need	12th Nov	11,219	9,619	9,146	95%	7,529	82%
LCM_2018_Nov_03	Cycle 1 and 2 users	13th Nov	13,408	10,923	9,443	86%	7,737	82%

7 DPD Rate - By Campaign

Campaign	Campaign Description	GMV				USER		
		Numerator	Denominator	7 DPD Rate	Baseline 7 DPD Rate	Numerator	Denominator	7 DPD Rate
LCM_2018_Nov_01	Exhaustion	1,163,649	15,457,053	7.5%	15.4%	606	9,452	6.4%
LCM_2018_Nov_02	BAU based on 2nd Highest need	509,429	11,228,285	4.5%	15.4%	366	8,339	4.4%
LCM_2018_Nov_03	Cycle 1 and 2 users	601,408	7,194,737	8.4%	15.4%	746	8,889	8.4%

15 DPD Rate - By Campaign

Campaign	Campaign Description	GMV				USER		
		Numerator	Denominator	15 DPD Rate	Baseline 15 DPD Rate	Numerator	Denominator	15 DPD Rate
LCM_2018_Nov_01	Exhaustion	721,523	15,423,290	4.7%	7.7%	327	9,408	3.5%
LCM_2018_Nov_02	BAU based on 2nd Highest need	254,777	11,098,015	2.3%	7.7%	182	8,198	2.2%
LCM_2018_Nov_03	Cycle 1 and 2 users	342,227	7,059,518	4.8%	7.7%	398	8,651	4.6%

30 DPD Rate - By Campaign

Campaign	Campaign Description	GMV				USER		
		Numerator	Denominator	30 DPD Rate	Baseline 30 DPD Rate	Numerator	Denominator	30 DPD Rate
LCM_2018_Nov_01	Exhaustion	476,552	15,290,132	3.1%	3.1%	185	9,252	2.0%
LCM_2018_Nov_02	BAU based on 2nd Highest need	137,670	10,699,588	1.3%	3.1%	85	7,783	1.1%
LCM_2018_Nov_03	Cycle 1 and 2 users	183,505	6,678,671	2.7%	3.1%	186	7,992	2.3%

EXTRACTION

Campaign	Campaign Description	OMPP			OM			CASH		
		PRE	POST	DIFF	PRE	POST	DIFF	PRE	POST	DIFF
LCM_2018_Nov_01	Exhaustion	78%	87%	9%	12%	7%	-5%	8%	5%	-3%
LCM_2018_Nov_02	BAU based on 2nd Highest need	66%	75%	9%	23%	16%	-7%	6%	5%	-1%
LCM_2018_Nov_03	Cycle 1 and 2 users	50%	73%	23%	31%	16%	-15%	15%	9%	-6%

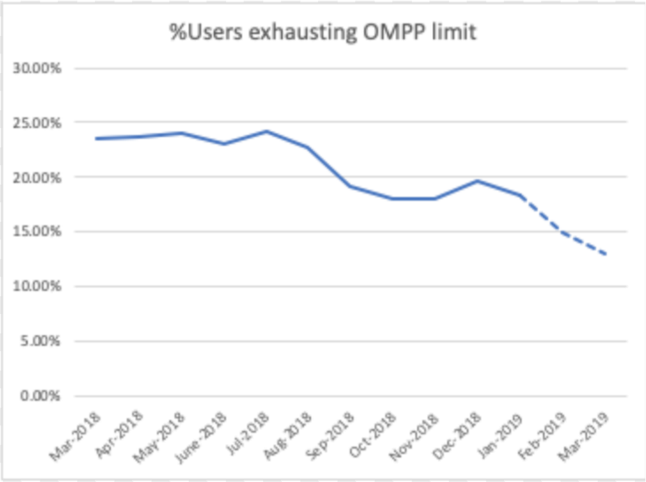
PENETRATION

Campaign	Campaign Description	OMPP			OM			CASH		
		PRE	POST	DIFF	PRE	POST	DIFF	PRE	POST	DIFF
LCM_2018_Nov_01	Exhaustion	79%	88%	9%	11%	6%	-4%	8%	4%	-3%
LCM_2018_Nov_02	BAU based on 2nd Highest need	68%	76%	8%	21%	16%	-6%	5%	5%	-1%
LCM_2018_Nov_03	Cycle 1 and 2 users	51%	73%	22%	30%	15%	-14%	15%	9%	-6%

Section 3.4

Current performance

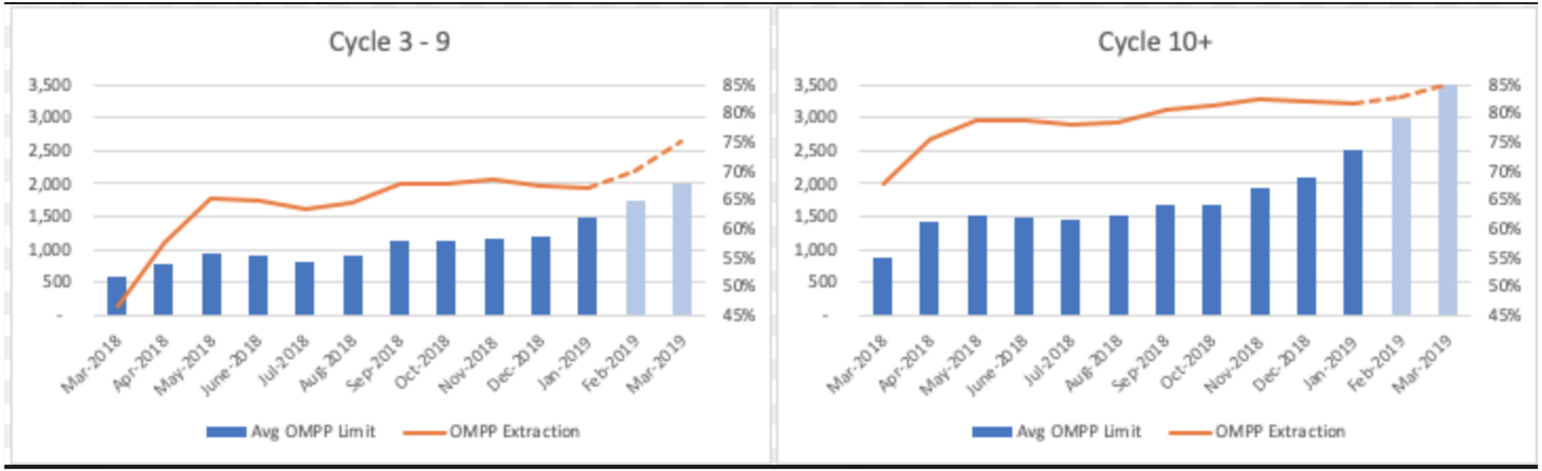
OMPP CLI - Impact on portfolio (1)



CLI Strategy:

- Strategy has undergone major modifications on new risk insights.
  - Learnings implemented led to realized drop of 75-80 basis points in 30dpd GMV rate (see above chart) currently at (2.3%) - significantly lower than portfolio avg (3.5%)
- % Users exhausting their OMPP (unmet credit need) has been consistently decreasing MoM.
  - Targeted 13% by March end. Currently at ~18%
- "Best risk" users will get higher limits to enable them to use OMPP for potential external merchant needs
- Automated bi-weekly CLI to be installed to reach steady state rule based line increases consistently every 2 weeks

OMPP CLI - Impact on portfolio (2)



Portfolio status on credit limit:

- Avg OMPP Limit for 10+cycle users has increased from ~1K to 2.5K so far. Targeted 4K by Mar-2019.
  - OMPP extraction for these users have increased from 68% to 82%. Targeted to reach 85% by Mar-2019
- Avg OMPP Limit for 3 to 9 cycle users have increased from ~0.5K to 1.5K so far. Targeted 2K by Mar-2019.
  - OMPP extraction for these users have increased from 47% to 67%. Targeted to reach 75% by March-2019
- Cycle 1 and 2 does not have line increases unless severe exhaustion use cases found.
  - Low and Grow discipline to control risk

Section 4

Collections

Collection Overview

- Collection comes at the end of credit life cycle and is one of the most important lever for managing the risk. An efficient collection strategy, helps in clearing caught-up capital, dispute resolution (and hence better NPS) and risk reduction
- Collection provides crucial feedbacks for building better strategy in underwriting/ Life cycle management and in improving the product. Eg. Customers from a particular geography or persona disputes (or threatens the collector); Repayment funnel sketcy.
- Two major business sub functions: Analytics and Ops. Analytics provides timely signals (proactive) and action strategy, Ops helps in effective execution (reactive)

Why does customer default? Major reasons are explained below:

Tried repayment but due to product downtime not able to repay

Forgot to repay

Emergency in Customers' life

Deterioration in financial health of customer

Product awareness: long term repercussion of default on availing future loans

Product proposition for the customer declines

Disputes with product or service

Fraudulent intent

From left to right, Low to High derogatory behaviour ⇒ Recovery propensity decreases, collection efforts change

Collections - (Decisions, Drivers, Actions)

1. Collections Strategy and Ops revolves around 3 Decisions that need to be taken:

Who	When	How
Which customer to take an action on collecting	When should this action be taken after the account becomes due	What action is to be taken to get the best return

For eg. if a credit card has been delinquent for 2 days then: Should we call after 2 days vs. send sms immediately vs. do nothing for 7 days (self cure)

2. Parameters that drive these 3 decisions are fundamentally:
- ROI - Collect back maximum amount with minimum cost of collection actions
- Effectiveness - Absolute collectability since bad debt should be minimized even if investment is needed
- NPS - Customer satisfaction during the collection process since it can always trigger attrition.

3. Postpaid specific collections action
- Actions: Push w/ fallback to SMS, SMS, IVR, Call, Field (Yet to start)
- Biz Functions: Analytics, Product, Operations
- Stakeholders: Internal, External 3rd party vendors

Section 4.1

Strategy

Collections Strategy

RePayment: ***f (connectability, efficiency, deterrents)***

1) Connectability: Push = (~82%), SMS = (~80%), IVR (~50%); Call = (~35%)

Strategies to improve connectability:

- Identify AM vs. PM preference of a customer for picking up manual calls
- Connect on alternate phone no. of the user from based on login activity on a dual SIM device
- Bureau based alternate contact info for bureau hits

2) Efficiency: Matching the delinquency stage with appropriate channel based on person of customer gives best efficiency

Strategies to improve efficiency:

- Actively source signals from sloppy payers who are given most effective collections action earlier than others
- Timing the actions from different channels based on previous repayment behavior (at a customer level)
- Month end surge in payments to be capitalised by launch of fixed cycle feature

3) Deterrent: Mobility need was the only deterrent till late payment got added starting Jan 2019

Strategies to add deterrents:

- Communication (true threat) of ola credit score in medium stage delinquency (30 - 60)
- Communication (false threat) of legal action in late stage delinquency (60-90)

Collection Strategy Impacted by

- Ride Behavior
  - Collection (from 0 - 15 days bucket) largely dependent on the customer ride need. Good deterrent.
  - Customer makes the payment, when (s)he is in the need for ride - 45% customers took ride in next 1 hours just after making repayment
  - With increase in use cases for Postpaid with external merchants, this will diminish
- Cycle of the customer
  - First 2 cycles customers show higher defaults compared to rest of the cycles
  - 10+ cycles, DPD values are constant. Returning and reliable customer with lowest risk profile
- Deterrents vs. Need case
  - No major deterrent to delay or skip payment. Industry uses late payment, credit bureau reporting etc
    - Late payment live on 90%+ population of postpaid
  - Ride/Mobility driven need to repay. Easy availability of alternate modes to travel when payment blocks Ola.
    - External merchant adoption to expand need.
  - Lack of strong contactability of customer. Phone number limits the reach.
    - Leveraging bureau for alternate contact. KYC based Upgrade ensures good contactability on high ticket loans
- Macro factors
  - Cabs supply scenario and drop in mobility need during festivals impacts repayments in those cohorts
  - Irregular riders on Ola (High ATS + LF) returning on OMPP during times of long weekends and bandhs cure slowly

Analytics (Strategy) ==> Actions (Ops)

Segments based on Cash/Cashless

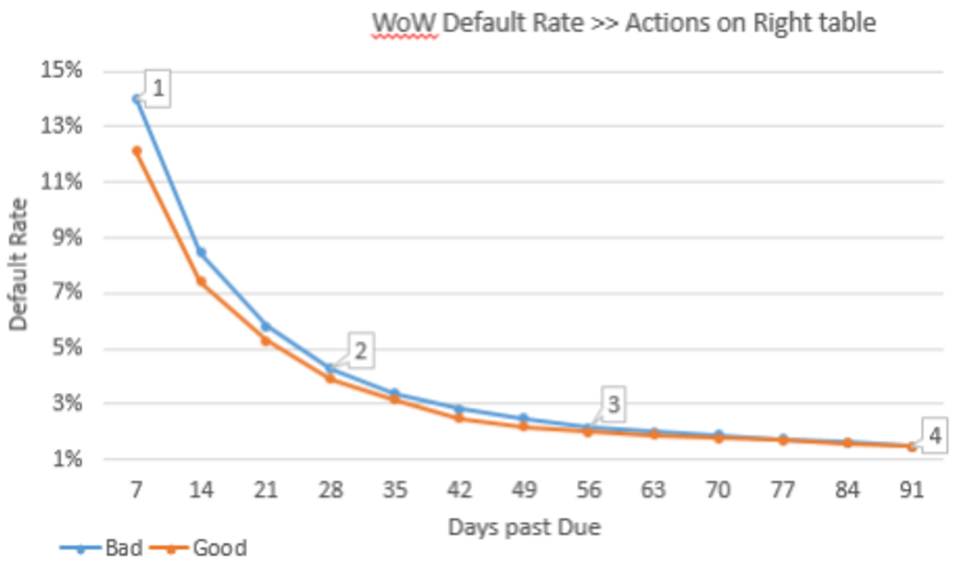
Tenure on OMPP (New Vs old)

Credit risk

Behavioral changes on Ola before/after OMPP activation

Credit risk change outside Ola (Bureau)

Analytics



Ops/Actions

1. Early indicator of risk suggests 7DPD is 2% higher than good week.

   RCA performed to identify segments which are not performing upto expectation.

   Specific action plan was devised
2. 28 DPD has gap of 0.5%, increased calling performed for specific segment
3. Based on action, bad rate conversion started reaching at 56 DPD level
4. Final impact at 91 DPD was 1BP. Then special actions was revoked

Section 4.2

Operations

Operations by Buckets - Lending in general

0 to 30 DPD*

- Communication starts from D-1 (1 day prior to default)
- Reminder messaging spaced at regular intervals - Basis customer frequency
- Modes of Communication
  - SMS
  - Email
  - Push
  - IVR
- Internal Calling team of 15 - better experience

30 to 60 DPD

- Increase in the frequency of communication
- Tonality also goes up
- Modes of Communication
  - SMS
  - Email
  - Push
  - IVR
- Outsourced to external agency with 15 agents
- Fully integrated environment

60 to 90 DPD

- Base outsources to 3rd party agency ideally to manage scaling up easily
- Commission based model in place
- Threat of Impact on Credit Score
- Communication in sync with the pitch from the agency
- SMS / IVR are placed at moderate intervals

90+ DPD

- Constitutes the Hard collection part
- External agency based calling
- Commission based model
- Severe threats and messaging opted
- SMS & IVR are also used for conveying high severity

*DPD is days past due

Collections Cadence in first 30 days

We have five communication channels to remind customers to repay their outstanding due.

DPD	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Outbound Call							>1000					>1000					>500					ALL			ALL					ALL	
SMS																															
PUSH																															
Email																															
IVR																															

__Push__

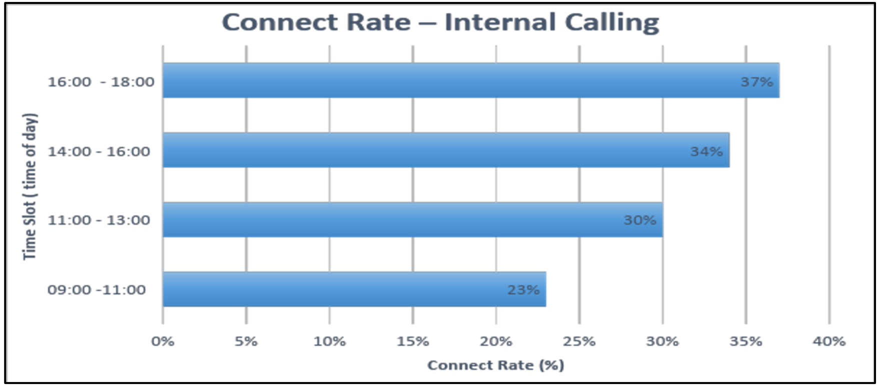
Rs.{{total_due_amount}} Ola Money Postpaid amount is due! Please pay by {{grace_date}} to avoid paying any late fee. Click here to pay now.

__SMS__

Your ₹{{total_due_amount}} Ola Money Postpaid amount is due since {{biling_cycle}}. Daily ₹{{per_day_fine}} late fee will be added to your Postpaid dues from today. Pay now to avoid more extra charges : http://bit.ly/2zeq7sV

Internal Calling Ops Performance

Week No	Agents Allocated	GMV for Connected Customers	Paid GMV from connect (excluded customers who paid due to need for ride) (A)	Paid % from Connect customers	GMV for non-connected customers	Paid GMV from non connect (excluded customers paid due to need for ride)	Paid % from Non connect customers	Cost of Collection (B)	GMV Recovered for every Rs1 spent (A/B)
W50	15	89,07,187	26,97,562	30.29%	2,29,64,029	13,86,880	6.04%	1,75,000	₹ 15.41
W51	15	87,32,516	20,89,616	23.93%	2,37,23,020	9,98,739	4.21%	1,75,000	₹ 11.94
W52	15	88,12,387	19,08,712	21.65%	2,20,16,876	8,22,656	3.74%	1,75,000	₹ 10.91
W1	15	72,30,381	12,82,339	17.74%	1,48,66,323	8,32,761	5.60%	1,75,000	₹ 7.33
W2	13	94,41,477	22,05,361	23.36%	1,75,08,322	9,80,173	5.60%	1,75,000	₹ 12.60
W3	13	88,05,576	22,56,722	25.64%	1,33,20,381	849,249	6.38%	1,75,000	₹ 12.90
W4	15	98,47,529	17,23,367	17.50%	2,25,67,402	9,09,592	4.03%	1,75,000	₹ 9.85
			1,41,63,679					12,25,000	₹ 11.56



For every rupee we put into outbound calling campaign , we recover Rs 11.5

Section 4.3

Capabilities

Channel Capabilities

Communication Channels

- SMS / Email / Push notifications
- IVR currently has been outsourced to 1Point1,
  - Daily capacity of **1L**, Fully integrated, can schedule SMS basis how much time customer has listened to script

Outbound calling Capacity

- 4 different set ups handling 4 different buckets
- 0 - 30 handled internally (**15 seats**, with auto-dailler)
- 30 - 60 with 1Point1, - **15 seats**
- 60 - 90 With Dhruv Agency - **10 seats**
- 90+ with Samaya Agency - **10 seats**

Payment is fixed cost structure

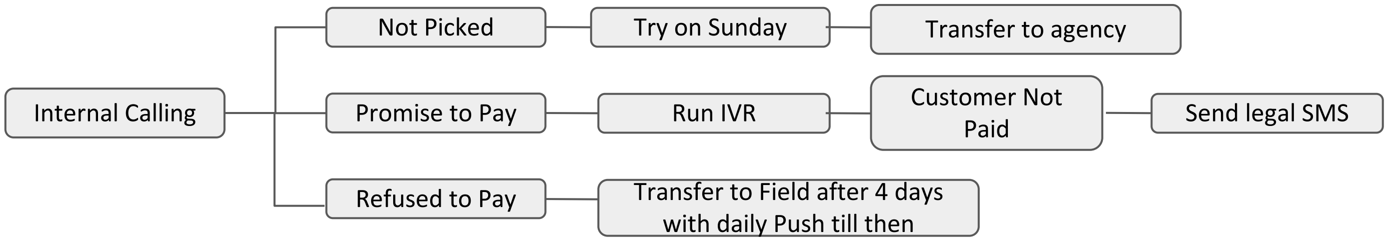
Payment is commission based structure on amount collected

Tool capabilities

Clevertap: Workflow management tool that is being used for sending ~65K reminders for collections daily

- Dynamic segmentation, trigger based real time contextual communication
- Integrated with Push/SMS/Email
- Integration of Call and IVR scheduled by Mar
- Realtime A/B testing & scale up of learnings
- Feedback looping through CRM to increase efficiency
- Easy to build decision rules → Fast to execute actions
- Plan to migrate all Late fees, Repayments, Fixed Cycle, Standing Instructions communications by Mar end

Example flow implemented on Clevertap



Reporting capabilities (MIS) - OFS MSTR

- MSTR, is being used for extensively as alert system and risk control tower in collection and measuring business health.
- All the delinquency related metrics are further segmented at Cash/Cashless on Ola (while Underwritten), Geography, number of cycle on OMPP etc.
    - These segmented measurement helps in understanding focus group of collection actions.

mmary | Top-7 Detail(Prev Day)

OLA Money

Rolling DPD Dashboard

From: 10/29/2018
To: 2/7/2019

Day of Week: -All- | Credit: -All- | Cycle: 10+... | Cashless Tag: cashless | Region: -All- | City: bangalore | Ride Frequency: -All-

GMV | Users | Abs't Users

Reporting Day	2/7/2019	2/6/2019	2/5/2019	2/4/2019	2/3/2019	2/2/2019	2/1/2019	1/31/2019	1/29/2019	1/28/2019	1/27/2019
Dpd	GMV	GMV	GMV	GMV	GMV	GMV	GMV	GMV	GMV	GMV	GMV
7	7.70%	8.33%	9.02%	9.08%	9.28%	9.13%	8.98%	8.85%	7.88%	7.75%	7.61%
14	4.30%	4.23%	4.35%	4.49%	4.60%	4.82%	4.92%	5.06%	4.71%	4.63%	4.55%
21	3.24%	3.09%	3.13%	3.18%	3.28%	3.23%	3.31%	3.43%	3.50%	3.51%	3.52%
28	2.35%	2.43%	2.51%	2.56%	2.59%	2.59%	2.53%	2.47%	2.47%	2.45%	2.47%
35	1.78%	1.83%	1.89%	1.91%	2.01%	2.02%	2.05%	2.12%	2.04%	2.06%	1.93%
42	1.59%	1.61%	1.61%	1.65%	1.58%	1.64%	1.65%	1.62%	1.78%	1.81%	1.94%
49	1.41%	1.46%	1.61%	1.64%	1.78%	1.82%	1.91%	1.91%	1.81%	1.81%	1.78%
56	1.67%	1.68%	1.62%	1.63%	1.60%	1.58%	1.53%	1.52%	1.63%	1.61%	1.63%
63	1.40%	1.44%	1.49%	1.45%	1.48%	1.55%	1.63%	1.77%	1.76%	1.74%	1.61%
70	1.62%	1.59%	1.59%	1.57%	1.48%	1.36%	1.26%	1.22%	1.22%	1.26%	1.33%

Product Capabilities (Interventions)

- Late Payment Fees
  - Customers to get 15 days + 7 days time to repay back the dues
  - Post 7 days, variable late payment fees to be applied basis balance due- Rs 1, Rs 2, Rs 3
  - Processes in place to take care of customer issues
- Live on External Merchants
  - Customers will be able to make payments on external merchants using Postpaid
  - Increase the use cases for Postpaid and reduce the dependency on Cabs
- Error Handling for Repayment
  - More intuitive repayment product flow
  - Customer to get real time update on issues, ride unblock to be handled to avoid customer issues
- Fixed Cycle
  - Currently cycle starts when customer takes the first ride and it's for next 15 days
  - Going forward, customers to be moved to two fixed cycles - 10th & 25th
  - Easier for customers to remember and make repayment on time, easier for managing calling

Strategy Formulation Capabilities (Learnings)

- Unbalanced growth
  - Too many new customer acquisition in short span leads to higher proportion of first cycle GMV
  - First cycle has higher defaults and thus leads to increase in overall defaults
  - The growth to be managed in balanced fashion while acquiring the customers
- Repayment Issues
  - Bug in the repayment funnel created impact on the collection, it impacted only certain Android app version that too customers who tried making repayment using "Saved Cards".
    - Tracking payment gateway success rates every week to keep track of each customer failure on repayment and quick reaction mechanism to handle such cases
- Customer Pain areas
  - Customers unhappy about certain issues, refuse to pay the due amount
  - Issues could be - Cancellation charges, driver denied duty, driver insisting on cash
  - Routing such cases back to In-House calling for better resolution

Section 4.4

Reporting & Monitoring

Collections Monitoring - Roll rate & Cure rate

Roll rate

- Weekly cohorts checked for 3 major milestones: 30, 60 and 90 DPD
- MSTR enables deep diving at a specific segment viz. "Mumbai collections affected by bandh on cash early adopters"
- Split by every 7 day buckets of DPD there is RCA at a granular level that helps decisive focused reaction to repayments

Cure rate

- Curing targets set using back calculating desired 30 DPD (eg. 3.5%): Green, Amber, Red for each 7 days curing period
- What works and what doesn't is constantly monitored to catch up with risk trends evolution
- Log of actions and impact maintained for streamlined learning

Weekly Collections Monitoring - Roll Rate

DPD	04-Feb	28-Jan	21-Jan	14-Jan	07-Jan	31-Dec	24-Dec	17-Dec	10-Dec	03-Dec	26-Nov	19-Nov	12-Nov	05-Nov	29-Oct	22-Oct
7	11.53%	10.92%	10.27%	10.72%	11.54%	11.62%	11.07%	10.33%	12.17%	14.11%	14.45%	20.13%	15.40%	12.11%	14.23%	14.01%
14	6.91%	6.96%	6.97%	6.82%	6.94%	7.73%	7.12%	8.46%	8.54%	8.93%	13.15%	10.40%	7.42%	8.63%	8.46%	8.74%
21	5.20%	5.36%	5.08%	5.03%	5.72%	5.64%	6.75%	6.55%	5.93%	9.20%	7.45%	5.27%	5.74%	5.80%	6.15%	5.70%
28	4.16%	4.07%	3.87%	4.27%	4.17%	5.31%	4.94%	4.55%	6.55%	5.75%	3.91%	4.32%	4.29%	4.63%	4.45%	4.37%
35	3.32%	3.18%	3.46%	3.14%	4.08%	4.03%	3.64%	5.07%	4.48%	3.14%	3.44%	3.39%	3.58%	3.49%	3.58%	3.31%
42	2.70%	3.02%	2.75%	3.45%	3.33%	3.13%	4.38%	3.78%	2.48%	2.81%	2.82%	2.96%	2.87%	2.94%	2.80%	2.52%
49	2.74%	2.51%	3.17%	3.01%	2.82%	4.00%	3.44%	2.20%	2.33%	2.47%	2.62%	2.52%	2.55%	2.41%	2.25%	2.15%
56	2.29%	2.97%	2.73%	2.51%	3.62%	3.06%	2.00%	2.07%	2.15%	2.38%	2.29%	2.30%	2.15%	2.01%	1.98%	1.89%
63	2.79%	2.58%	2.26%	3.32%	2.82%	1.88%	1.94%	2.01%	2.15%	2.14%	2.15%	2.02%	1.87%	1.83%	1.80%	1.69%
70	2.38%	2.08%	3.05%	2.65%	1.77%	1.84%	1.86%	2.05%	1.99%	2.05%	1.93%	1.78%	1.74%	1.71%	1.63%	1.50%
77	1.91%	2.79%	2.46%	1.71%	1.73%	1.74%	1.87%	1.86%	1.92%	1.82%	1.71%	1.68%	1.65%	1.53%	1.45%	1.33%
84	2.47%	2.23%	1.59%	1.64%	1.63%	1.74%	1.71%	1.77%	1.65%	1.62%	1.63%	1.59%	1.43%	1.34%	1.24%	1.40%
91	1.96%	1.46%	1.52%	1.47%	1.60%	1.55%	1.62%	1.51%	1.45%	1.52%	1.55%	1.33%	1.24%	1.14%	1.29%	1.35%

30	3.85%	3.71%	3.57%	3.95%	3.85%	4.98%	4.00%	4.85%	5.98%	4.88%	3.32%	4.26%	3.92%	4.12%	4.21%	3.96%
60	2.42%	2.97%	2.04%	3.23%	3.33%	2.15%	1.89%	2.11%	2.11%	2.23%	2.27%	2.07%	2.06%	1.86%	1.89%	1.80%
91	1.96%	1.46%	1.52%	1.47%	1.60%	1.55%	1.62%	1.51%	1.45%	1.52%	1.55%	1.33%	1.24%	1.14%	1.29%	1.35%

Percentage of customers moved to higher delinquency bucket on weekly basis

Portfolio Collections Reporting - Curing Rates

	04-Feb	28-Jan	21-Jan	14-Jan	07-Jan	31-Dec	24-Dec	17-Dec	10-Dec	03-Dec	26-Nov	Avg Curing %
7_14	36.80%	32.20%	35.00%	40.90%	40.30%	30.20%	31.10%	30.50%	39.50%	38.20%	34.70%	35.40%
14_21	25.40%	23.10%	25.50%	27.50%	26.00%	20.80%	20.20%	23.30%	33.60%	30.00%	28.40%	25.80%
21_28	22.40%	20.00%	23.10%	25.30%	26.10%	21.30%	24.60%	23.30%	28.80%	22.80%	25.80%	23.95%
28_35	18.40%	17.80%	19.00%	24.70%	23.20%	18.40%	20.00%	22.60%	22.10%	19.70%	20.40%	20.57%
35_42	15.20%	12.80%	12.40%	15.40%	17.40%	14.00%	13.60%	15.60%	21.00%	18.30%	16.80%	15.68%
42_49	9.30%	8.80%	8.10%	9.60%	9.90%	8.70%	9.00%	11.30%	17.10%	12.40%	11.50%	10.52%
49_56	8.90%	6.40%	9.30%	11.00%	9.50%	11.00%	9.10%	11.20%	13.00%	9.20%	9.10%	9.79%
56_63	6.20%	5.70%	10.00%	8.30%	7.80%	6.00%	6.30%	6.50%	9.70%	6.60%	6.50%	7.24%
63_70	7.50%	7.70%	8.10%	6.00%	5.90%	5.20%	7.50%	4.70%	7.00%	4.70%	4.50%	6.25%
70_77	8.30%	8.70%	7.20%	3.40%	6.00%	6.50%	8.80%	6.50%	6.30%	5.70%	3.90%	6.48%
77_84	11.20%	9.50%	7.00%	5.20%	6.30%	7.00%	8.10%	7.80%	9.30%	5.30%	3.00%	7.25%
84_91	12.00%	7.90%	7.30%	9.80%	8.00%	9.40%	8.50%	8.50%	10.50%	6.70%	2.50%	8.28%
7_28	61.20%	64.80%	66.70%	61.40%	59.60%	56.40%	65.00%	68.50%	67.50%	62.70%	67.70%	63.77%
28_56	45.20%	44.10%	44.70%	44.80%	44.70%	46.80%	48.80%	52.10%	49.90%	48.60%	48.50%	47.11%
56_91	35.90%	26.80%	26.60%	31.60%	32.80%	32.30%	29.60%	29.80%	27.90%	23.20%	18.00%	28.59%

- ➢ Current 7 DPD is trending at **10-11%**
- ➢ Current recovery rate is at **88.5%** from 7 DPD to 91 DPD
- ➢ **~65%** of amount cures from 7 to 28 DPD
- ➢ Similarly **~50%** of amount cures from 28 to 56 DPD
- ➢ **~30%** amount cures from 56 to 91 DPD

The percentage of amount recovered from delinquent accounts in each 7 day curing period

MoM Roll Rate and Cure Rate

30/60/90 DPD numbers at monthly level

Month	30 DPD	60 DPD	90 DPD
May'18	3.29%	2.32%	1.47%
Jun'18	5.12%	2.64%	2.03%
July'18	3.66%	2.10%	1.58%
Aug'18	3.57%	1.83%	1.27%
Sep'18	3.59%	1.74%	1.37%
Oct'18	3.98%	2.11%	1.59%
Nov'18	3.97%	2.07%	1.55%
Dec'18	5.01%	2.85%	
Jan'19	3.77%		

Bucket wise curing rate at monthly level

Month	<30 DPD	31-60 DPD	61-90 DPD
May'18	96.71%	29.48%	36.64%
Jun'18	94.88%	48.44%	23.11%
July'18	96.34%	42.62%	24.76%
Aug'18	96.43%	48.74%	30.60%
Sep'18	96.41%	51.53%	21.26%
Oct'18	96.02%	46.98%	24.64%
Nov'18	96.03%	47.86%	25.12%
Dec'18	94.99%	43.11%	
Jan'19	96.23%		

Jun - single cash campaign with just 4K activations
Oct - cash activations started to flow in (continues in Nov)
Dec - Due to holidays
Jan - Pre-cash levels of risk in spite of 35% activations from cash (late fee benefits)

Section 4.5

Current Performance

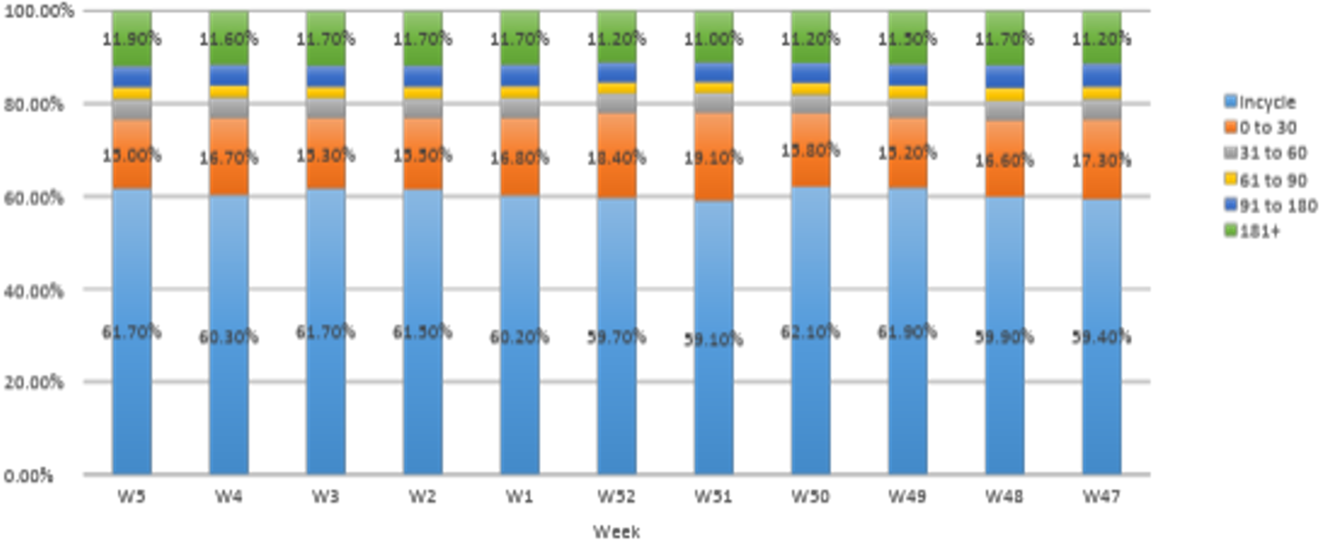
Monthly Collections Cohorts

Month	GMV in CR	M-1**	M	M+1	M+2	M+3	M+4	M+5	M+6	M+7	M+8
May'18	46.00	7.05%	86.90%	96.05%	97.76%	98.15%	98.23%	98.28%	98.29%	98.32%	98.34%
Jun'18	52.41	7.64%	87.76%	97.41%	98.21%	98.59%	98.68%	98.70%	98.74%	98.75%	
Jul'18	53.66	7.23%	87.54%	97.53%	98.43%	98.85%	98.96%	98.99%	99.01%		
Aug'18	54.57	7.33%	88.54%	97.53%	98.48%	98.82%	98.96%	98.99%			
Sep'18	53.96	7.56%	87.00%	97.24%	98.11%	98.63%	98.74%				
Oct'18	58.06	9.37%	90.12%	97.24%	98.22%	98.64%					
Nov'18	48.44	13.99%	88.24%	96.39%	97.65%						
Dec'18	69.10	20.97%	89.71%	97.18%							
Jan'19	73.60	20.41%	91.11%	**97.75%***							
Feb'19	89.00	**22.00%***	**91.80%***								

** Projected numbers for February and March based on curing rate and late fee roll-out population being 95% in Feb’19*

***M-1 is payment received before due date (i.e within 15 days of cycle start date till Nov’19. After softblock was introduced in Dec’19, this is pmts within 22 days of cycle start date)*

Portfolio Risk Reporting - Business Health

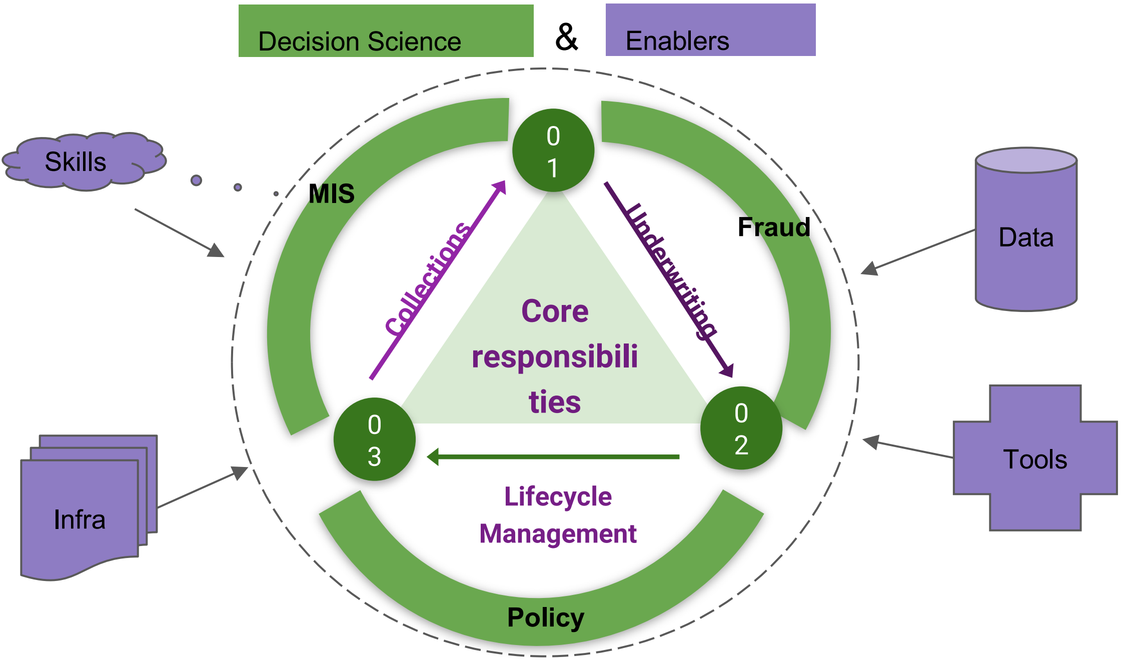


- GMV distribution, should be skewed towards in-cycle and <=30 days past due.
- Over the period 181+ contribution should be decreasing (after write-off).
- OMPP book is consistent across the expected segment. 181+ is not shrinking as there is no write-off done of all the past 181+, which is contributing to major chunk of 181+ days past due

Section 5

Enabling Entities

Enabling Entities - How they impact Decision Science



Skills: In a constantly changing lending landscape,leaders who have seen complete lending cycle (both peak and downturn) bring much needed preparedness for unseen future. Xperience across other regions, multiple credit products and credit life cycles is valuable.

Data: Data is the new currency. Bringing new insights from traditional data (using ML) or using unexplored non-traditional data is key in beating competition. Being Fintech OFS needs to be on top of Data based intelligence for survival.

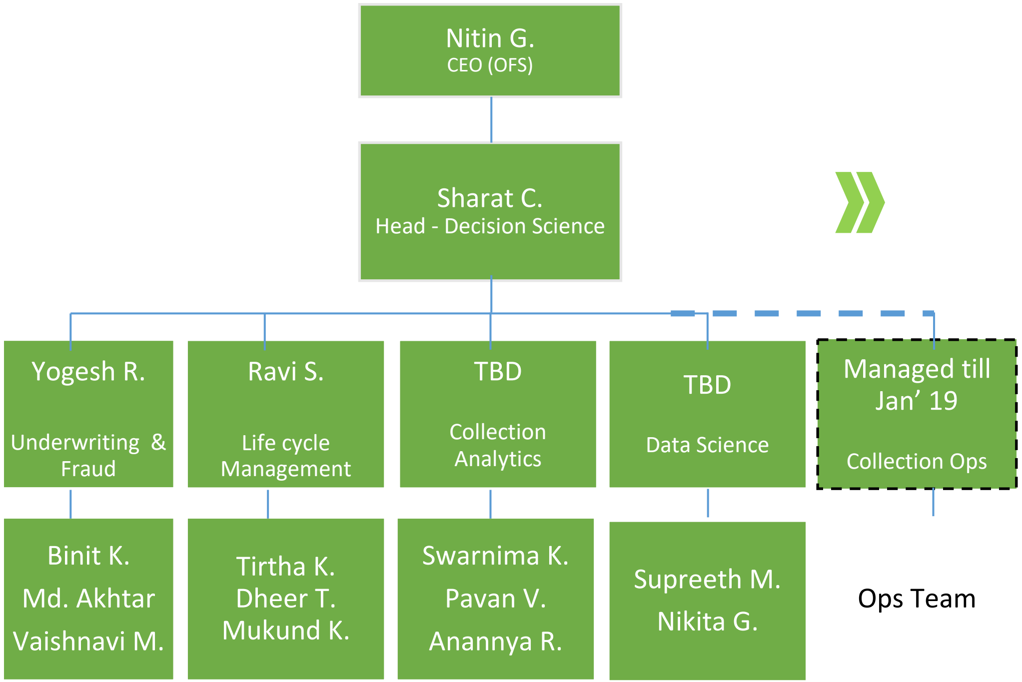
Tools: Tools help us make smarter and efficient decisions. Being new to industry semi automated processes are good to start off but given regulatory compliance tools will be needed sooner than later.

Infra: Infra helps scale-up, which is much needed for any business more so in a financial environment where speed of decisions without errors is a must have.

Section 5.1

Team Profile and Skills

Decision Science Team - Profile and Skills



Experience: 11 yrs in credit risk; SE Asia+EMEA+US markets;

Risk: Modeling, Strategy, Bureau score dev, Tools and Applications

Products: All unsecured lending, Deposits, Mortgage

Experience: Combined 10 yrs in credit risk; EMEA+US markets;

Risk: Indian Bureau, Data Science, Risk Policy

Products: Fintech lending, Credit cards, Personal Loans, SME

Experience: Combined 25 yrs; 15 in credit risk;

Domain: Data Science, U/W, LCM, Collections, Fraud, Marketing

Section 5.2

Data Sources

Ola data - Relevance to lending business

Ability to Pay	Intent to Pay	Contactability
➢ Premium Savvy (Preferred mode of Sedan on ola) ➢ Propensity of being cashless in taking rides ➢ Ride intent (Work, geo location based tagging of tech parks) ➢ Total spend on transportation ➢ Avg recharge on Ola wallet ➢ Airport, outstation, rental trips frequency and value ➢ Income estimator model that predicts income from pure Ola data variables, with incremental value on bureau data	➢ Repayment behavior on Ola Postpaid ➢ Device fingerprinting ➢ CC/DC ride payment behavior ➢ Wifi based social/employment proxies ➢ Geo location based ride activity in high credit risk pincodes ➢ Gender (algo based) ➢ Customer rating on app ➢ Customer dispute type	➢ Phone number actively used ➢ IMEI/Google ID ➢ Saved favorites in locations ➢ Nearby residence communities ➢ Loyalty (Higher confidence on contactability)

Alternate data

- Other than Bureau, Trusting social (leading telecom Bureau in SE Asia), Payback (Subsidiary of Amex), Zeotap (major telecom operators as data partners) and LinkedIn are being explored
- Most of the tradition banks, are able to crack risk for Bureau hit population and hence risk for this particular segment. Banks are still dependent on salary slip/balance statement to predict capacity to pay.
- Industry Example: Kabbage, leading SME lending Fintech in US, underwrites loan from $500-$250K line in <7mins, by doing data alliance with Yodlee/Paypal to predict capacity to pay.
- Alt data - Positions Fintech to Improve risk, Reduce CAC, Optimise Revenue

Trusting Social	• Pilot is performed, data didn't help much in the pilot stage.
Payback	• Payback captures loyalty points related information on debit as well as credit card, It has association with Amazon, Flipkart, Bigbazar, ICICI, Indusland etc. which provides great opportunity to understand New to credit customers (Customers' doesn't have CC) • Current Stage: data exercise will happen by 4th week of Feb'19
LinkedIn	• LinkedIn provides great opportunity to understand customers' capacity to pay metrics, which will inturn help in automating product (specially for higher lines). • Current stage: Initial phases of discussion
Zeotap	• Zeotap contains targeting data by different merchants, which further provides proxy for customers propensity to buy product and hence it can be good predictor of customers' affluence

Section 5.3

Tools

Tools in OFS Decision Science

Data Science Tool

R, Python, Hive: All of these are open-source tools and don't have any licensing cost but do have small maintenance cost. These tools are enabler for analysts to find insights, build models etc.

Decision Engine

Business Rule Engine: This will enable us to make automated decisions in future for customers in live environment, which may be used at underwriting, credit line increase.

Communication Engine

Clevertap: This tool helps us to send communications, roll-out campaigns at customer segment level and hence, enables us to test hypothesis and as well roll-out full fledged campaigns

Monitoring Tool

MSTR: This tool enables us to monitor key business and risk metric for each phase of customer lifecycle in real-time basis.

For collections, a risk tower has been built to identify early trends in risk deterioration

Section 5.4

Infrastructure

Infrastructure which helps us scale

Hue/hive Database

Hue Database:
Owing to inbuilt capabilities of hue, it's scalable with controlled cost.

Efficiency & Scaling Up

Presto & Zeppelin:
Presto will bring efficiency into interactive queries.

Zeppelin is a open source notebook feature that make it easy to share and document across analysts

Automation

Automation:
Schedulers and workflows inbuilt in hive have enabled us to automate our decision models, strategy and decision making process

Data lake

Data lake:
OFS has created an comprehensive list of ~1500 chars, based on bookings history, transaction history, usage of different payment modes. All of these chars are generated automatically every month and enables us to make quick and sharp decisions

OMPP Current stage >> OMPP stage by April’19

	Policy	Model	Strategy	Tracking
Current Stage	Semi-Automated	Semi-Automated	Semi-Automated	Semi-Automated
By April ’19	Fully- Automated	Fully- Automated	Semi-Automated*	Fully Automated

Has no dependency on external tools/applications. It is driven by internal Data PE and dedicated data lake owners within OFS

* Strategy requires many A/B testing to mature. Also, strategy keeps on changing due to changing business scenario. Therefore, for evolving lenders, automating it is very difficult

Appendix

Weekly collections Tracking Contd.

Cash Customers ; Cycle 1,2

DPD	04-Feb	28-Jan	21-Jan	14-Jan	07-Jan	31-Dec	24-Dec	17-Dec	10-Dec
7	30.73%	27.93%	29.26%	27.86%	29.70%	33.24%	36.14%	14.74%	27.37%
14	22.68%	24.42%	23.60%	23.40%	26.76%	31.93%	11.90%	22.86%	25.05%
21	20.82%	20.39%	19.92%	22.06%	28.68%	10.77%	20.77%	22.04%	12.22%
28	18.13%	18.24%	19.42%	24.40%	9.28%	19.14%	20.50%	11.27%	16.24%
35	16.35%	17.85%	22.14%	8.54%	17.93%	18.82%	10.74%	14.60%	9.90%
42	16.43%	20.77%	8.02%	17.02%	17.99%	10.23%	13.22%	8.94%	7.64%
49	20.03%	7.56%	16.31%	17.56%	9.74%	12.71%	9.05%	6.54%	7.45%
56	7.12%	15.88%	16.90%	9.30%	12.11%	8.46%	5.85%	6.82%	11.64%
63	15.54%	16.74%	8.74%	11.79%	8.29%	5.75%	6.90%	11.50%	8.12%
70	16.52%	8.39%	11.40%	8.18%	5.51%	6.45%	10.93%	8.12%	8.10%
77	8.09%	10.66%	7.95%	5.50%	6.45%	10.82%	6.94%	8.10%	10.95%
84	9.93%	7.70%	5.15%	6.45%	10.73%	6.94%	7.46%	10.95%	14.97%
91	7.02%	4.94%	6.01%	10.43%	6.73%	6.78%	11.13%	14.97%	19.16%

30	16.52%	17.97%	19.62%	21.37%	10.46%	19.67%	16.48%	13.77%	13.35%
60	11.40%	18.38%	8.95%	12.70%	9.24%	7.35%	5.39%	9.29%	10.25%
91	7.02%	4.94%	6.01%	10.43%	6.73%	6.78%	11.13%	14.97%	19.16%

Cashless Customers ; Cycle 1,2

DPD	04-Feb	28-Jan	21-Jan	14-Jan	07-Jan	31-Dec	24-Dec	17-Dec	10-Dec
7	15.67%	15.91%	16.33%	16.35%	19.56%	22.19%	21.15%	14.51%	16.93%
14	11.12%	11.49%	11.52%	12.91%	15.44%	15.51%	9.87%	11.70%	11.98%
21	8.92%	8.87%	9.89%	11.61%	12.18%	7.77%	9.50%	9.45%	7.23%
28	6.95%	7.99%	9.09%	9.52%	6.16%	7.91%	7.85%	5.91%	9.60%
35	6.48%	7.39%	7.77%	4.85%	6.46%	6.72%	5.07%	7.99%	7.14%
42	6.36%	6.93%	4.38%	5.62%	6.15%	4.52%	7.24%	6.24%	4.65%
49	6.34%	4.05%	5.12%	5.75%	4.18%	6.82%	5.83%	4.33%	4.70%
56	3.74%	4.87%	5.43%	3.77%	6.38%	5.39%	4.00%	4.37%	4.59%
63	4.68%	5.23%	3.44%	5.91%	5.12%	3.83%	4.17%	4.34%	4.46%
70	4.97%	3.22%	5.49%	4.88%	3.69%	4.02%	4.10%	4.29%	4.27%
77	3.00%	5.13%	4.52%	3.59%	3.86%	3.96%	3.98%	4.05%	3.69%
84	4.60%	4.10%	3.43%	3.70%	3.76%	3.74%	3.87%	3.42%	3.62%
91	3.72%	3.19%	3.49%	3.38%	3.51%	3.54%	3.20%	3.37%	3.29%

30	6.58%	7.83%	8.48%	8.27%	5.70%	7.98%	5.85%	6.88%	9.19%
60	3.91%	5.85%	3.31%	5.45%	5.87%	3.89%	4.15%	4.42%	4.39%
91	3.72%	3.19%	3.49%	3.38%	3.51%	3.54%	3.20%	3.37%	3.29%

Weekly Collections Tracking Contd.

Cash Customers ; Cycle 2+

DPD	**04-Feb**	**28-Jan**	21-Jan	14-Jan	07-Jan	31-Dec	24-Dec	17-Dec	10-Dec
7	8.65%	7.53%	7.46%	8.03%	8.94%	9.58%	7.10%	8.35%	9.66%
14	4.44%	4.36%	5.10%	5.50%	6.02%	4.17%	6.47%	7.45%	7.14%
21	3.45%	4.10%	3.98%	4.58%	3.35%	3.94%	6.58%	5.78%	4.90%
28	3.37%	3.37%	3.46%	2.14%	2.76%	5.54%	4.61%	3.78%	5.17%
35	2.65%	2.96%	1.57%	2.14%	4.14%	3.40%	3.01%	4.82%	5.60%
42	2.48%	1.41%	1.94%	3.74%	3.17%	2.71%	3.58%	5.60%	3.27%
49	1.37%	1.92%	3.57%	2.76%	2.34%	3.58%	5.50%	2.98%	0.34%
56	1.92%	3.51%	2.43%	2.34%	2.47%	5.17%	2.98%	0.34%	3.21%
63	3.51%	2.37%	2.34%	2.11%	5.17%	2.98%	0.34%	3.21%	3.71%
70	2.37%	1.94%	2.02%	5.11%	2.98%	0.34%	3.21%	3.71%	2.41%
77	1.94%	2.02%	4.16%	2.95%	0.34%	3.21%	3.71%	2.23%	4.05%
84	1.51%	3.92%	2.66%	0.34%	3.21%	3.71%	2.23%	4.05%	4.84%
91	3.47%	2.66%	0.34%	2.95%	3.71%	1.52%	4.05%	4.09%	0.88%

30	3.60%	3.72%	2.24%	2.16%	2.70%	4.77%	4.25%	3.90%	6.01%
60	1.82%	3.77%	1.71%	3.48%	3.72%	2.61%	2.26%	1.74%	4.93%
91	3.47%	2.66%	0.34%	2.95%	3.71%	1.52%	4.05%	4.09%	0.88%

Cashless Customers ; Cycle 2+

DPD	**04-Feb**	**28-Jan**	21-Jan	14-Jan	07-Jan	31-Dec	24-Dec	17-Dec	10-Dec
7	10.14%	9.49%	8.76%	9.37%	10.26%	10.21%	9.78%	9.83%	10.85%
14	5.61%	5.72%	5.91%	5.72%	5.74%	6.64%	6.75%	7.41%	7.81%
21	4.10%	4.47%	4.19%	4.01%	4.76%	5.33%	5.79%	5.91%	5.57%
28	3.37%	3.28%	3.05%	3.43%	3.88%	4.39%	4.29%	4.16%	5.88%
35	2.64%	2.47%	2.75%	2.85%	3.19%	3.42%	3.24%	4.42%	4.09%
42	2.05%	2.36%	2.48%	2.61%	2.71%	2.73%	3.76%	3.41%	2.16%
49	2.11%	2.25%	2.38%	2.40%	2.43%	3.39%	3.07%	1.88%	1.96%
56	2.04%	2.19%	2.13%	2.14%	3.02%	2.71%	1.71%	1.72%	1.76%
63	2.02%	1.99%	1.91%	2.75%	2.47%	1.59%	1.59%	1.64%	1.82%
70	1.80%	1.74%	2.51%	2.31%	1.49%	1.50%	1.51%	1.72%	1.71%
77	1.58%	2.27%	2.14%	1.42%	1.40%	1.39%	1.56%	1.58%	1.74%
84	2.00%	1.94%	1.31%	1.32%	1.30%	1.44%	1.44%	1.60%	1.45%
91	1.69%	1.20%	1.21%	1.17%	1.32%	1.30%	1.46%	1.32%	1.25%
30	3.14%	2.95%	2.77%	3.28%	3.45%	4.13%	3.53%	4.24%	5.42%
60	1.89%	2.26%	1.71%	2.62%	2.92%	1.88%	1.56%	1.73%	1.76%
91	1.69%	1.20%	1.21%	1.17%	1.32%	1.30%	1.46%	1.32%	1.25%

Solves to reduce Fraud (30 to 50 BP) from current 90+ rate of 1.5%

Current Fraud Framework:

- User present on Ola platform with multiple profiles
  - This is identified using their multiple fingerprints (imei, google advt id, android id)
- Fraudulent practice identified on their current Ola Money account

Enhancements being built in Fraud Framework:

- Identify the users whose primary phone number(sourced from bureau) is not same as phone number registered with Ola
- Identify the users whose any device fingerprint matches with any driver’s device fingerprint
- Identify the users who are using same credit card/ debit card number or same UPI handles as 90 days past due user on Ola platform
- Identify the geolocations who have high concentration of 90 days past due users
- Identify the wifi mac address who have high concentration of 90 days past due users
- Identify the users who have logged into significantly high number of devices in last 3 month
- Identify the users whose devices have significantly high number of signups in last 3 months

Overall portfolio risk is being maintained in three segments:

- Cost of experimentation: This is the cost to unlock new target groups (cash cycle 1 & 2 users). Loss rates are expected to be higher than the matured portfolio. But, the contribution to overall portfolio losses are quite low. This is quite important in order to keep unlocking new segment of customers
- Cost of acquisition: This is the cost of acquiring new customers. This is always expected to be slightly higher than matured portfolio. This is also important to keep the business growth intact.
- Cost of bad debt: This is the usual losses expected in lending business

90DPD GMV rates (segment wise)

Segments	Before Late Fine	After Late Fine
Cash Cycle 1 & 2	6.7%	6.1%
Cashless Cycle 1 & 2	2.9%	2.2%
All customers Cycle 3+	1.3%	0.9%

Segment contribution to overall portfolio 90dpd

Segments	Before Late Fine	After Late Fine
Cash Cycle 1 & 2	0.13%*	0.24%
Cashless Cycle 1 & 2	0.39%	0.26%
All customers Cycle 3+	1.06%	0.70%
Total	**1.58%**	**1.20%**