

# **Capstone Project:**

## **Advanced Data analytics**

### **CRISTIAN TORRES BARON**

#### **Project Overview:**

This capstone analyzes Lending Club loans to support an investment decision. An investment firms plans to invest \$10M and hired me to evaluate **loan quality and risk** before selecting loans.

Dataset: (downloaded from Lending Club loan data). Scope is limited to **year 2015, 36-month loans, and credit card debt purpose**. The dataset contains **7,151 loans** and **16 variables** (borrower, loan, and credit attributes).

Column	Description
<b>id</b>	A unique LC assigned ID for the loan listing.
<b>member_id</b>	A unique LC assigned ID for the borrower member.
<b>term</b>	The number of payments on the loan. Values are in months and can be either 36 or 60.
<b>purpose</b>	A category provided by the borrower for the loan request.
<b>loan_status</b>	Current status of the loan
<b>loan_amnt</b>	The listed amount of the loan applied for by the borrower. If at some point in time, the credit department reduces the loan amount, then it will be reflected in this value.
<b>int_rate</b>	Interest Rate on the loan
<b>installment</b>	The monthly payment owed by the borrower if the loan originates.
<b>home_ownership</b>	The home ownership status provided by the borrower during registration or obtained from the credit report. Our values are: RENT, OWN, MORTGAGE, OTHER
<b>annual_inc</b>	The self-reported annual income provided by the borrower during registration.
<b>verification_status</b>	Indicates if income was verified by LC, not verified, or if the income source was verified
<b>revol_bal</b>	Total credit revolving balance
<b>revol_util</b>	Revolving line utilization rate, or the amount of credit the borrower is using relative to all available revolving credit.
<b>total_acc</b>	The total number of credit lines currently in the borrower's credit file
<b>acc_open_past_24mths</b>	Number of trades opened in past 24 months.
<b>total_pymnt</b>	Payments received to date for total amount funded

### **Specific problem to solve:**

**Identify which loans are most suitable for investment by predicting default risk and estimating expected losses/returns**, so the firm can build a loan portfolio that **maximizes expected return while controlling risk**.

### **What this project delivers:**

- Exploratory analysis to understand borrower/loan patterns and risk drivers
- Data cleaning + feature engineering based on the provided variables/data dictionary
- A predictive model (risk scoring) to estimate probability of default / loan quality
- A portfolio selection recommendation for allocating the **\$10M** toward lower-risk, higher-expected-value loans\

# Step 1 – Data preparation & Exploratory Analysis

This step covers the first phase of the capstone: prepare the Lending Club 2015 dataset and run initial exploratory analysis to confirm the data is reliable for modeling default risk and building a \$10M investment portfolio. Because the dataset comes from a public source and is already structured, the focus is on validation, cleaning, and understanding risk patterns.

## CHANGELOG DATASET INGEST, VALIDATION, CLEANING:

Ingest the RAW data

id	member_id	term	purpose	loan_status	loan_amnt	int_rate	installment	home_owvr	annual_inc	verification	revol_bal	revol_util	total_acc	acc_open	total_pymnt
2	6286683	66483442	36 months	credit_card	Fully Paid	24000	7.89	750.86 MORTGAGE	237500	Source Verified	28279	36.9	25	5	24948.45
3	46314315	49422035	36 months	credit_card	Fully Paid	8000	6.68	245.85 RENT	41000	Not Verified	24377	51	29	2	8551.63
4	51256140	54741593	36 months	credit_card	Fully Paid	12175	9.17	388.13 MORTGAGE	100000	Not Verified	21312	64.8	17	3	13299.91
5	42984750	45981489	36 months	credit_card	Charged Off	6400	6.92	197.83 RENT	41500	Source Verified	14936	73.2	15	1	3550.38
6	42181434	45139159	36 months	credit_card	Fully Paid	12000	6.68	387.22 OWN	73000	Not Verified	20024	20.7	25	4	13125.77
7	38457385	41251256	36 months	credit_card	Fully Paid	9000	8.67	284.82 MORTGAGE	82000	Verified	46158	77.1	29	2	9789.87
8	61943001	66135720	36 months	credit_card	Fully Paid	3500	8.18	109.97 MORTGAGE	80000	Source Verified	40641	27.7	63	8	3703.95
9	65905100	70609838	36 months	credit_card	Fully Paid	8000	7.89	250.29 OWN	47840	Source Verified	8019	46.9	11	3	8351.54
10	51256140	54515885	36 months	credit_card	Charged Off	6000	7.89	187.72 RENT	43000	Source Verified	3102	50.9	20	3	1701.25
11	55461218	59062933	36 months	credit_card	Fully Paid	6000	8.18	188.52 RENT	33000	Verified	9425	62.4	32	3	6457
12	53734742	57275484	36 months	credit_card	Charged Off	10000	10.99	327.34 RENT	36000	Source Verified	9022	67.8	49	4	3594.63
13	63364494	67706221	36 months	credit_card	Fully Paid	10000	5.32	301.15 RENT	110000	Source Verified	10412	45.3	24	1	10243.02
14	38658348	41442230	36 months	credit_card	Fully Paid	21000	6.03	639.15 OWN	55000	Source Verified	21083	68.5	19	2	22163.26
15	41079352	43955683	36 months	credit_card	Charged Off	16000	18.25	580.45 RENT	65000	Not Verified	15460	58.8	17	6	8662.4
16	40360663	45415401	36 months	credit_card	Fully Paid	34000	6.24	108.93 MORTGAGE	250000	Source Verified	34720	36.5	38	2	9337.71
17	43955321	46972042	36 months	credit_card	Fully Paid	6800	14.65	234.57 MORTGAGE	50000	Not Verified	26212	78.2	27	10	7542.84
18	57713792	61466545	36 months	credit_card	Fully Paid	25000	7.26	774.91 MORTGAGE	120000	Not Verified	24385	44.6	38	6	26176.01
19	40962381	43838261	36 months	credit_card	Fully Paid	7500	7.89	234.65 MORTGAGE	50000	Source Verified	7142	84	12	1	7965.96777
20	55545027	59146796	36 months	credit_card	Fully Paid	5600	9.17	178.53 MORTGAGE	130000	Verified	5028	14	29	9	5824.08
21	43420028	46446765	36 months	credit_card	Charged Off	12000	17.57	431.25 RENT	60000	Source Verified	16084	76.5	14	4	6850.96
22	43480116	46506869	36 months	credit_card	Fully Paid	24000	9.17	765.1 RENT	80000	Source Verified	20341	69.4	27	3	26006.83
23	40363063	43227900	36 months	credit_card	Fully Paid	6000	9.49	192.17 RENT	60000	Source Verified	7290	38	31	5	6405.75
24	66595145	71320993	36 months	credit_card	Fully Paid	16800	7.26	520.74 MORTGAGE	55000	Source Verified	15292	37	37	2	17467.63
25	54533710	58114430	36 months	credit_card	Fully Paid	10000	12.69	335.45 RENT	105000	Not Verified	9391	82	10	7	11009.02
26	67458304	72270094	36 months	credit_card	Fully Paid	15621	11.99	518.93 RENT	34000	Source Verified	16100	55.1	37	3	15631.77
27	38505940	41299744	36 months	credit_card	Fully Paid	16000	8.19	502.79 RENT	52000	Not Verified	10723	45.6	18	1	17566.02
28	43480048	46506869	36 months	credit_card	Fully Paid	10000	13.23	392.83 MORTGAGE	60000	Source Verified	10000	77.6	11	4	10690.14
29	43295451	46556372	36 months	credit_card	Fully Paid	8000	13.33	270.83 MORTGAGE	54000	Source Verified	2379	15.7	17	7	8155.32
30	63558275	67912987	36 months	credit_card	Charged Off	6325	15.41	220.54 MORTGAGE	72500	Source Verified	3197	55.1	17	5	0
31	40197818	43602355	36 months	credit_card	Fully Paid	18000	11.99	597.78 MORTGAGE	80000	Not Verified	13747	61.4	44	7	18956.07
32	38699542	41484365	36 months	credit_card	Fully Paid	30000	6.99	926.18 MORTGAGE	180000	Source Verified	159886	43.8	40	5	32498.7
33	61473698	65592561	36 months	credit_card	Charged Off	3000	15.61	104.9 RENT	21000	Verified	5297	79.1	17	4	797.01
34	40380675	43245399	36 months	credit_card	Charged Off	15000	12.39	501.02 RENT	65000	Not Verified	12767	66.2	24	4	7954.57
35	46809202	49957173	36 months	credit_card	Fully Paid	6000	10.99	196.41 RENT	111500	Source Verified	33435	72.5	11	2	6533.91
36	63246010	67597774	36 months	credit_card	Fully Paid	19200	5.32	578.21 MORTGAGE	135000	Not Verified	34725	25.2	33	6	20067.55

# Profiling Dataset if contain Null Values

Here use a simple function to handle if the data set contain blanks and the total % of this using and convert the root data in a functional table

## Missing Count

- =COUNTBLANK(Table1)

## Total Rows

- =ROWS(Table1)

# Filtering

The **cell total\_pymnt** column contained invalid values represented as "--" or zero. Since a loan cannot be charged off without any payment history, these values were treated as missing data. Rows with missing total payment values were removed to maintain data consistency and analytical validity.

## Data types & Standardization

The screenshot shows a Microsoft Excel spreadsheet with a data table. The table has 36 rows and 17 columns. The columns are labeled C through S. The first few columns (C-D) represent categorical variables like 'term' and 'purpose'. Columns E-S represent numerical variables like 'loan\_amnt', 'int\_rate', and 'total\_pymnt'. A column 'missing\_count' is present in the last row (S) and is highlighted in green. The 'verification\_status' column contains values like 'Source Verified' and 'Not Verified'. The 'revol\_util' column shows percentages like 789.00%. The 'annual\_inc' column shows large numerical values like 237500. The 'total\_pymnt' column shows large numerical values like 24948.45.

## Data type fixes (convert to true numeric)

### Currency fields converted to numeric

- Columns: **loan\_amnt, installment, annual\_inc, revol\_bal, total\_pymnt**
- Before: risk of being stored as text due to \$ and separators.
- After: true numeric values; currency format applied only for display.

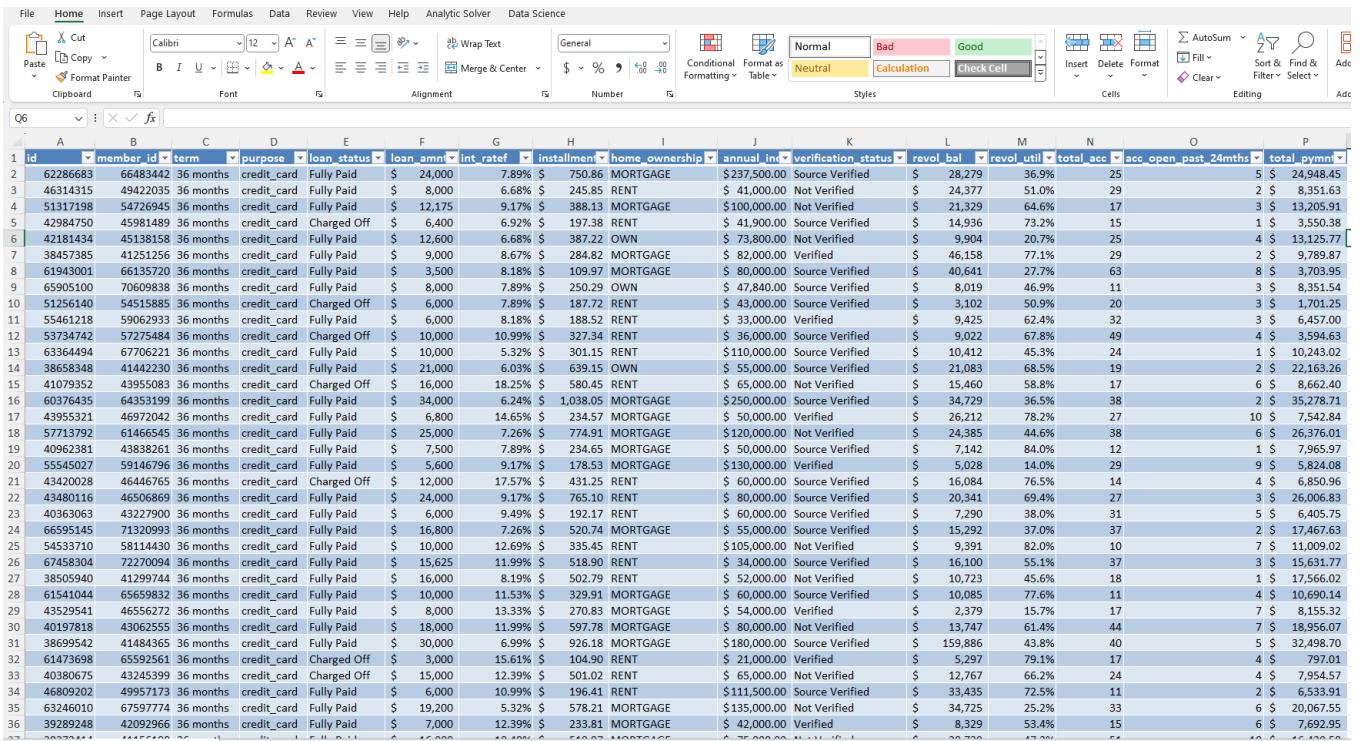
### Percent fields corrected (scale + format)

- Columns: **int\_rate, revol\_util**
- Before: percent stored as text or scaled incorrectly (e.g., 789% instead of 7.89%).

- After: correct numeric percent values (e.g., 7.89%), not multiplied by 100.

## IDs preserved

- Columns: id, member\_id
- Before: risk of scientific notation or losing precision.
- After: protected formatting (text or full numeric without scientific notation).



The screenshot shows a Microsoft Excel spreadsheet titled 'Q6'. The top menu bar includes File, Home, Insert, Page Layout, Formulas, Data, Review, View, Help, Analytic Solver, and Data Science. The ribbon tabs are Home, Insert, Page Layout, Formulas, Data, Review, View, Help, Analytic Solver, and Data Science. The Home tab is selected, showing options for Cut, Copy, Paste, Format Painter, Font, Alignment, Number, Styles, Cells, and Editing. The table below has 26 columns labeled A through P. Column A is 'id', column B is 'member\_id', and column C is 'term'. Other columns include 'purpose', 'loan\_status', 'loan\_amnt', 'int\_rate', 'installment', 'home\_ownership', 'annual\_inc', 'verification\_status', 'revol\_bal', 'revol\_util', 'total\_acc', 'acc\_open\_past\_24mths', and 'total\_pymnt'. The data consists of approximately 36 rows of financial records, such as credit card usage and mortgage payments.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	id	member_id	term	purpose	loan_status	loan_amnt	int_rate	installment	home_ownership	annual_inc	verification_status	revol_bal	revol_util	total_acc	acc_open_past_24mths	total_pymnt
2	62286683	66483442	36 months	credit_card	Fully Paid	\$ 24,000	7.89%	\$ 750.86	MORTGAGE	\$ 237,500.00	Source Verified	\$ 28,279	36.9%	25	5	\$ 24,948.45
3	46314315	49422035	36 months	credit_card	Fully Paid	\$ 8,000	6.68%	\$ 245.85	RENT	\$ 41,000.00	Not Verified	\$ 24,377	51.0%	29	2	\$ 35,151.63
4	51317198	54726945	36 months	credit_card	Fully Paid	\$ 12,175	9.17%	\$ 388.13	MORTGAGE	\$ 100,000.00	Not Verified	\$ 21,329	64.6%	17	3	\$ 13,205.91
5	42984750	45981489	36 months	credit_card	Charged Off	\$ 6,400	6.92%	\$ 197.38	RENT	\$ 41,900.00	Source Verified	\$ 14,936	73.2%	15	1	\$ 3,550.38
6	42181434	45138158	36 months	credit_card	Fully Paid	\$ 12,600	6.68%	\$ 387.22	OWN	\$ 73,800.00	Not Verified	\$ 9,904	20.7%	25	4	\$ 13,125.77
7	38457385	41251256	36 months	credit_card	Fully Paid	\$ 9,000	8.67%	\$ 284.82	MORTGAGE	\$ 82,000.00	Verified	\$ 46,158	77.1%	29	2	\$ 9,789.87
8	61943001	66135720	36 months	credit_card	Fully Paid	\$ 3,500	8.18%	\$ 109.97	MORTGAGE	\$ 80,000.00	Source Verified	\$ 40,641	27.7%	63	8	\$ 3,703.95
9	65905104	70609838	36 months	credit_card	Fully Paid	\$ 8,000	7.89%	\$ 250.29	OWN	\$ 47,840.00	Source Verified	\$ 8,019	46.9%	11	6	\$ 8,351.54
10	51256140	54515885	36 months	credit_card	Charged Off	\$ 6,000	7.89%	\$ 187.72	RENT	\$ 43,000.00	Source Verified	\$ 3,102	50.9%	20	3	\$ 1,701.25
11	55461218	59062933	36 months	credit_card	Fully Paid	\$ 6,000	8.18%	\$ 188.52	RENT	\$ 33,000.00	Verified	\$ 9,425	62.4%	32	3	\$ 6,457.00
12	53734742	57275484	36 months	credit_card	Charged Off	\$ 10,000	10.99%	\$ 327.34	RENT	\$ 36,000.00	Source Verified	\$ 9,022	67.8%	49	4	\$ 3,594.63
13	63364494	67706221	36 months	credit_card	Fully Paid	\$ 10,000	5.32%	\$ 301.15	RENT	\$ 110,000.00	Source Verified	\$ 10,412	45.3%	24	1	\$ 10,243.02
14	38658348	41442230	36 months	credit_card	Fully Paid	\$ 21,000	6.03%	\$ 639.15	OWN	\$ 55,000.00	Source Verified	\$ 21,083	68.5%	19	2	\$ 22,163.26
15	41079352	43955083	36 months	credit_card	Charged Off	\$ 16,000	18.25%	\$ 580.45	RENT	\$ 65,000.00	Not Verified	\$ 15,460	58.8%	17	6	\$ 8,662.40
16	60376435	64353199	36 months	credit_card	Fully Paid	\$ 34,000	6.24%	\$ 1,038.05	MORTGAGE	\$ 250,000.00	Source Verified	\$ 34,729	36.5%	38	2	\$ 35,278.71
17	43955321	46972042	36 months	credit_card	Fully Paid	\$ 6,800	14.65%	\$ 234.57	MORTGAGE	\$ 50,000.00	Verified	\$ 26,212	78.2%	27	10	\$ 7,542.84
18	57713792	61466545	36 months	credit_card	Fully Paid	\$ 25,000	7.26%	\$ 774.91	MORTGAGE	\$ 120,000.00	Not Verified	\$ 24,385	44.6%	38	6	\$ 26,376.01
19	40962381	43838261	36 months	credit_card	Fully Paid	\$ 7,500	7.89%	\$ 234.65	MORTGAGE	\$ 50,000.00	Source Verified	\$ 7,142	84.0%	12	1	\$ 7,965.97
20	55545027	59146796	36 months	credit_card	Fully Paid	\$ 5,600	9.17%	\$ 178.53	MORTGAGE	\$ 130,000.00	Verified	\$ 5,028	14.0%	29	9	\$ 5,824.08
21	43420028	46446765	36 months	credit_card	Charged Off	\$ 12,000	17.57%	\$ 431.25	RENT	\$ 60,000.00	Source Verified	\$ 16,084	76.5%	14	4	\$ 6,850.96
22	43480116	46506869	36 months	credit_card	Fully Paid	\$ 24,000	9.17%	\$ 765.10	RENT	\$ 80,000.00	Source Verified	\$ 20,341	69.4%	27	3	\$ 26,006.83
23	40363063	43227900	36 months	credit_card	Fully Paid	\$ 6,000	9.49%	\$ 192.17	RENT	\$ 60,000.00	Source Verified	\$ 7,290	38.0%	31	5	\$ 4,605.75
24	66595145	71320993	36 months	credit_card	Fully Paid	\$ 16,800	7.26%	\$ 520.74	MORTGAGE	\$ 55,000.00	Source Verified	\$ 15,292	37.0%	37	2	\$ 17,467.63
25	54533710	58114430	36 months	credit_card	Fully Paid	\$ 10,000	12.69%	\$ 335.45	RENT	\$ 105,000.00	Not Verified	\$ 9,391	82.0%	10	7	\$ 11,009.02
26	67458304	72270094	36 months	credit_card	Fully Paid	\$ 15,625	11.99%	\$ 518.90	RENT	\$ 34,000.00	Source Verified	\$ 16,100	55.1%	37	3	\$ 15,631.77
27	38505940	41299744	36 months	credit_card	Fully Paid	\$ 16,000	8.19%	\$ 502.79	RENT	\$ 52,000.00	Not Verified	\$ 10,723	45.6%	18	1	\$ 17,566.02
28	61541044	65659832	36 months	credit_card	Fully Paid	\$ 10,000	11.53%	\$ 329.91	MORTGAGE	\$ 60,000.00	Source Verified	\$ 10,085	77.6%	11	4	\$ 10,690.14
29	43529541	46556272	36 months	credit_card	Fully Paid	\$ 8,000	13.33%	\$ 270.83	MORTGAGE	\$ 54,000.00	Verified	\$ 2,379	15.7%	17	7	\$ 8,155.32
30	40197818	43062555	36 months	credit_card	Fully Paid	\$ 18,000	11.99%	\$ 597.78	MORTGAGE	\$ 80,000.00	Not Verified	\$ 13,747	61.4%	44	7	\$ 18,956.07
31	38699542	41484365	36 months	credit_card	Fully Paid	\$ 30,000	6.99%	\$ 926.18	MORTGAGE	\$ 180,000.00	Source Verified	\$ 159,886	43.8%	40	5	\$ 32,498.70
32	61473698	65592561	36 months	credit_card	Charged Off	\$ 3,000	15.61%	\$ 104.90	RENT	\$ 21,000.00	Verified	\$ 5,297	79.1%	17	4	\$ 797.01
33	40380675	43245399	36 months	credit_card	Charged Off	\$ 15,000	12.39%	\$ 501.02	RENT	\$ 65,000.00	Not Verified	\$ 12,767	66.2%	24	4	\$ 7,954.57
34	46809202	49957173	36 months	credit_card	Fully Paid	\$ 6,000	10.99%	\$ 196.41	RENT	\$ 111,500.00	Source Verified	\$ 33,435	72.5%	11	2	\$ 6,533.91
35	63246010	67597774	36 months	credit_card	Fully Paid	\$ 19,200	5.32%	\$ 578.21	MORTGAGE	\$ 135,000.00	Not Verified	\$ 34,725	25.2%	33	6	\$ 20,067.55
36	39289248	42092966	36 months	credit_card	Fully Paid	\$ 7,000	12.39%	\$ 233.81	MORTGAGE	\$ 42,000.00	Verified	\$ 8,329	53.4%	15	6	\$ 7,692.95

## Preparing for Analytical y EDA

### Default label created

Using Logical function can transform the categorical values for the EDA (Data modeling) “=IF(E2="Fully Paid",0,1)”

- Before: loan\_status only as text.
- After: default\_flag:
  - Charged Off = 1
  - Fully Paid = 0

Also for home\_ownership

(=IFS(J2="MORTGAGE",1,J2="RENT",0,J2="OWN",2))

- MORTAGAGE = 1
- RENT = 0
- OWN = 2

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
1	id	member_id	term	purpose	label_loan	loan_amnt	int_rate	installment	home_ownership	ownership_label	annual_inc	verification	revol_bal	revol_util	total_acc	acc_open_p	
2	62286683	66483442	36 months	credit_card	Fully Paid	0 \$ 24,000	7.89%	\$ 750.86	MORTGAGE	1 \$	237,500.00	Source Verified	\$ 28,279	36.9%	25	5	
3	46314315	49422035	36 months	credit_card	Fully Paid	0 \$ 8,000	6.68%	\$ 245.85	RENT	0 \$	41,000.00	Not Verified	\$ 24,377	51.0%	29	2	
4	51317198	54726945	36 months	credit_card	Fully Paid	0 \$ 12,175	9.17%	\$ 388.13	MORTGAGE	1 \$	100,000.00	Not Verified	\$ 21,329	64.6%	17	3	
5	42984750	45981489	36 months	credit_card	Charged Off	1 \$ 6,400	6.92%	\$ 197.38	RENT	0 \$	41,900.00	Source Verified	\$ 14,936	73.2%	15	1	
6	42181434	45138158	36 months	credit_card	Fully Paid	0 \$ 12,600	6.68%	\$ 387.22	OWN	2 \$	73,800.00	Not Verified	\$ 9,904	20.7%	25	4	
7	38457385	41215126	36 months	credit_card	Fully Paid	0 \$ 9,000	8.67%	\$ 284.82	MORTGAGE	1 \$	82,000.00	Verified	\$ 46,158	77.1%	29	2	
8	61943001	66135720	36 months	credit_card	Fully Paid	0 \$ 3,500	8.18%	\$ 109.97	MORTGAGE	1 \$	80,000.00	Source Verified	\$ 40,641	27.7%	63	8	
9	65905100	70609838	36 months	credit_card	Fully Paid	0 \$ 8,000	7.89%	\$ 250.29	OWN	2 \$	47,840.00	Source Verified	\$ 8,019	46.9%	11	3	
10	51256140	54515885	36 months	credit_card	Charged Off	1 \$ 6,000	7.89%	\$ 187.72	RENT	0 \$	43,000.00	Source Verified	\$ 3,102	50.9%	20	3	
11	55461218	59062933	36 months	credit_card	Fully Paid	0 \$ 6,000	8.18%	\$ 188.52	RENT	0 \$	33,000.00	Verified	\$ 9,425	62.4%	32	3	
12	53734742	57275484	36 months	credit_card	Charged Off	1 \$ 10,000	10.99%	\$ 327.34	RENT	0 \$	36,000.00	Source Verified	\$ 9,022	67.8%	49	4	
13	63364494	67706221	36 months	credit_card	Fully Paid	0 \$ 10,000	5.32%	\$ 301.15	RENT	0 \$	110,000.00	Source Verified	\$ 10,412	45.3%	24	1	
14	38658348	41442230	36 months	credit_card	Fully Paid	0 \$ 21,000	6.03%	\$ 639.15	OWN	2 \$	55,000.00	Source Verified	\$ 21,083	68.5%	19	2	
15	41079352	43955083	36 months	credit_card	Charged Off	1 \$ 16,000	18.25%	\$ 580.45	RENT	0 \$	65,000.00	Not Verified	\$ 15,460	58.8%	17	6	
16	60376435	64353199	36 months	credit_card	Fully Paid	0 \$ 34,000	6.24%	\$ 1,038.05	MORTGAGE	1 \$	250,000.00	Source Verified	\$ 34,729	36.5%	38	2	
17	43955321	46972042	36 months	credit_card	Fully Paid	0 \$ 6,800	14.65%	\$ 234.57	MORTGAGE	1 \$	50,000.00	Verified	\$ 26,212	78.2%	27	10	
18	57713792	61466545	36 months	credit_card	Fully Paid	0 \$ 25,000	7.26%	\$ 774.91	MORTGAGE	1 \$	120,000.00	Not Verified	\$ 24,385	44.6%	38	6	
19	40962381	43838261	36 months	credit_card	Fully Paid	0 \$ 7,500	7.89%	\$ 234.65	MORTGAGE	1 \$	50,000.00	Source Verified	\$ 7,142	84.0%	12	1	
20	55545027	59146796	36 months	credit_card	Fully Paid	0 \$ 5,600	9.17%	\$ 178.53	MORTGAGE	1 \$	130,000.00	Verified	\$ 5,028	14.0%	29	9	
21	43420028	46446765	36 months	credit_card	Charged Off	1 \$ 12,000	17.57%	\$ 431.25	RENT	0 \$	60,000.00	Source Verified	\$ 16,084	76.5%	14	4	
22	43480116	46506869	36 months	credit_card	Fully Paid	0 \$ 24,000	9.17%	\$ 765.10	RENT	0 \$	80,000.00	Source Verified	\$ 20,341	69.4%	27	3	
23	40363063	43227900	36 months	credit_card	Fully Paid	0 \$ 6,000	9.49%	\$ 192.17	RENT	0 \$	60,000.00	Source Verified	\$ 7,290	38.0%	31	5	
24	66595145	71320993	36 months	credit_card	Fully Paid	0 \$ 16,800	7.26%	\$ 520.74	MORTGAGE	1 \$	55,000.00	Source Verified	\$ 15,292	37.0%	37	2	
25	54533710	58114430	36 months	credit_card	Fully Paid	0 \$ 10,000	12.69%	\$ 335.45	RENT	0 \$	105,000.00	Not Verified	\$ 9,391	82.0%	10	7	
26	67458304	72270094	36 months	credit_card	Fully Paid	0 \$ 15,625	11.99%	\$ 518.90	RENT	0 \$	34,000.00	Source Verified	\$ 16,100	55.1%	37	3	
27	38505940	41299744	36 months	credit_card	Fully Paid	0 \$ 16,000	8.19%	\$ 502.79	RENT	0 \$	52,000.00	Not Verified	\$ 10,723	45.6%	18	1	
28	61514044	65659832	36 months	credit_card	Fully Paid	0 \$ 10,000	11.53%	\$ 329.91	MORTGAGE	1 \$	60,000.00	Source Verified	\$ 10,085	77.6%	11	4	
29	43529541	46556277	36 months	credit_card	Fully Paid	0 \$ 8,000	13.33%	\$ 270.83	MORTGAGE	1 \$	54,000.00	Verified	\$ 2,379	15.7%	17	7	
30	40197818	43062555	36 months	credit_card	Fully Paid	0 \$ 18,000	11.99%	\$ 597.78	MORTGAGE	1 \$	80,000.00	Not Verified	\$ 13,747	61.4%	44	7	
31	38699542	41484365	36 months	credit_card	Fully Paid	0 \$ 30,000	6.99%	\$ 926.18	MORTGAGE	1 \$	180,000.00	Source Verified	\$ 159,886	43.8%	40	5	
32	61473698	65592561	36 months	credit_card	Charged Off	1 \$ 3,000	15.61%	\$ 104.90	RENT	0 \$	21,000.00	Verified	\$ 5,297	79.1%	17	4	
33	4030675	43245399	36 months	credit_card	Charged Off	1 \$ 15,000	12.39%	\$ 501.02	RENT	0 \$	65,000.00	Not Verified	\$ 12,767	66.2%	24	4	
34	46809202	49957173	36 months	credit_card	Fully Paid	0 \$ 6,000	10.99%	\$ 196.41	RENT	0 \$	111,500.00	Source Verified	\$ 33,435	72.5%	11	2	
35	63246010	6759774	36 months	credit_card	Fully Paid	0 \$ 19,200	5.32%	\$ 578.21	MORTGAGE	1 \$	135,000.00	Not Verified	\$ 34,725	25.2%	33	6	
36	39289248	42092966	36 months	credit_card	Fully Paid	0 \$ 7,000	12.39%	\$ 233.81	MORTGAGE	1 \$	42,000.00	Verified	\$ 8,329	53.4%	15	6	

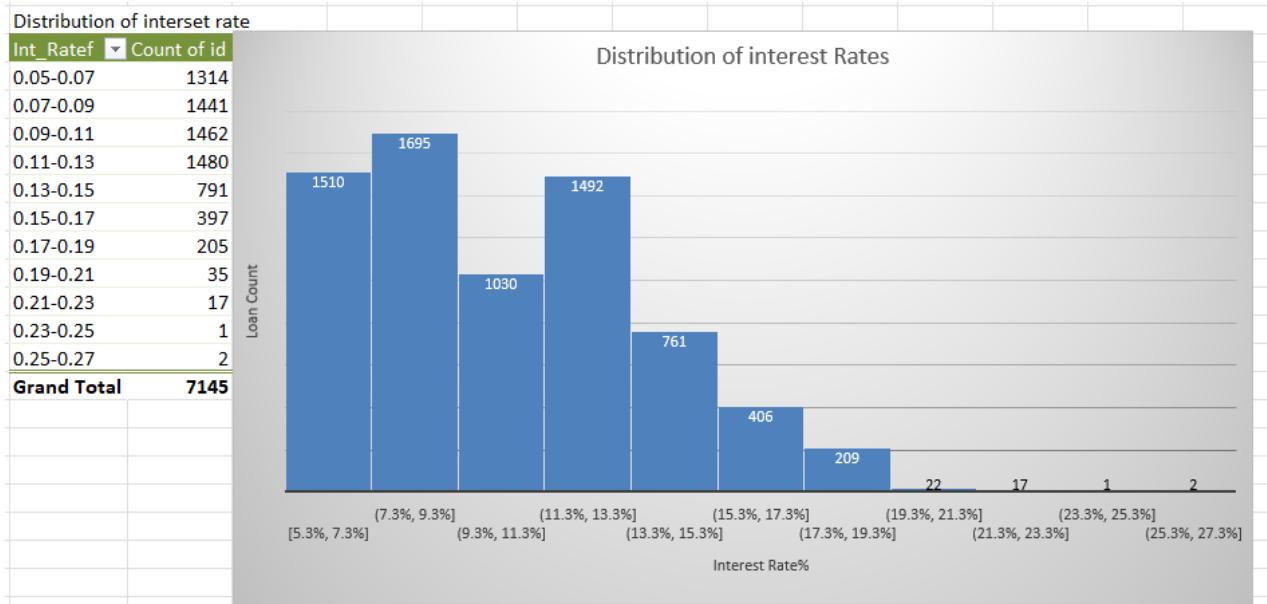
## Step 2 Exploratory analysis

### Pivot table to prepare analysis Pre-Modeling

#### Objective

Use pivot tables to identify patterns related to loan default risk and validate that cleaned variables behave as expected before modeling. And based in the core business question **“Which loans should we select to maximize return while minimizing default risk?”**

#### First analyze the distribution of interest rate

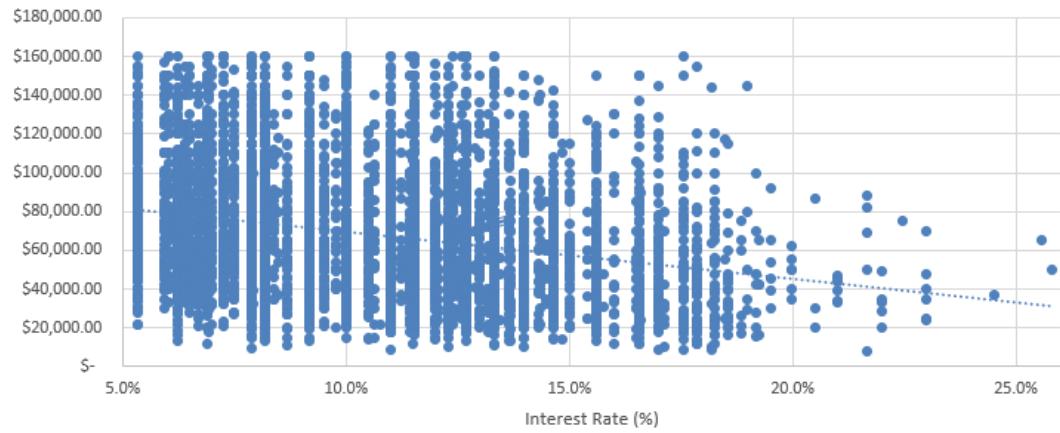


Interest rates were grouped into 2-percentage-point bins ranging from 5% to 27% using Excel Pivot Table grouping. Rates are stored as decimal values and displayed as percentages for interpretability. The distribution

shows a strong concentration between 7% and 13%, indicating that most loans fall within moderate interest rate ranges.

## Relationship between variables

Relationship Between Annual Income and Interest Rate



	Annual_inc	Percentile
0	\$ 41,000.00	KEEP
1	\$ 100,000.00	KEEP
0	\$ 41,900.00	KEEP
2	\$ 73,800.00	KEEP
1	\$ 82,000.00	KEEP
1	\$ 80,000.00	KEEP
2	\$ 47,840.00	KEEP
0	\$ 43,000.00	KEEP
0	\$ 33,000.00	KEEP
0	\$ 36,000.00	KEEP
0	\$ 110,000.00	KEEP
2	\$ 55,000.00	KEEP
0	\$ 65,000.00	KEEP
1	\$ 50,000.00	KEEP
1	\$ 120,000.00	KEEP
1	\$ 50,000.00	KEEP
1	\$ 130,000.00	KEEP
0	\$ 60,000.00	KEEP
0	\$ 80,000.00	KEEP
0	\$ 60,000.00	KEEP
1	\$ 55,000.00	KEEP
0	\$ 105,000.00	KEEP
0	\$ 34,000.00	KEEP
0	\$ 52,000.00	KEEP
1	\$ 60,000.00	KEEP
1	\$ 54,000.00	KEEP
1	\$ 80,000.00	KEEP
0	\$ 21,000.00	KEEP
0	\$ 65,000.00	KEEP
0	\$ 111,500.00	KEEP
1	\$ 135,000.00	KEEP
1	\$ 42,000.00	KEEP
1	\$ 75,000.00	KEEP
1	\$ 65,000.00	KEEP
0	\$ 121,000.00	KEEP
1	\$ 48,000.00	KEEP
0	\$ 55,000.00	KEEP

The variable (annual\_inc) exhibited a right-skewed distribution with a small number of extreme high-income values (outliers)

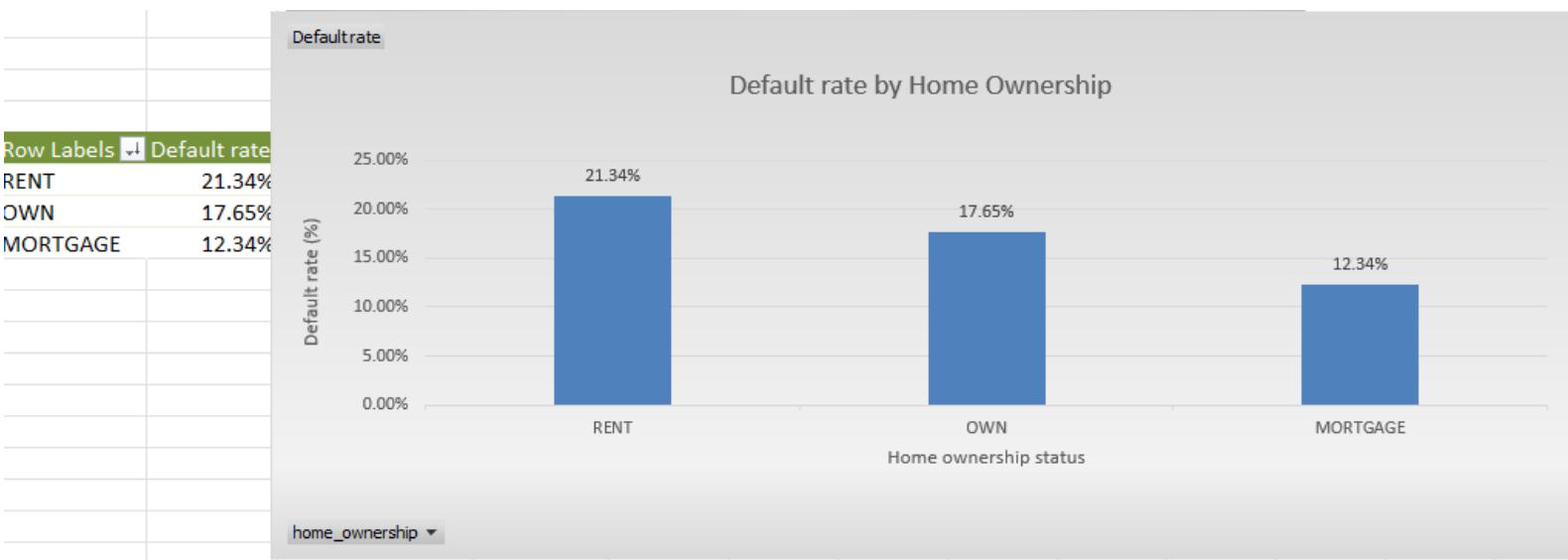
Rather than using an arbitrary cutoff, income values above the **95<sup>th</sup> percentile** (approximately at \$160,000) **were removed only for visualization purposes**, preserving the natural income range for the majority of observations using logical functions such (=PERCENTIL.INC) and binning the interest rates.

After that A **scatter plot** was used to visualize the relationship between **annual\_inc** and **int\_rate** after removing income values above the 95th percentile.

The visualization shows a **negative relationship**: borrowers with higher income generally receive lower interest rates, while lower-income borrowers are charged higher rates. Although the relationship is not perfectly linear, the trend aligns with expected credit-risk pricing behavior.

## Default rate by Home Ownership

Compare **default behavior** across **home ownership** categories to assess borrower stability and investment risk



A PivotTable and bar chart were used to compare default rates across home ownership categories. Renters exhibit higher default rates than borrowers with mortgages or owned homes, suggesting that home ownership is associated with lower credit risk and greater financial stability.

## Step 3 Performing predictive analytics

First using Analytic Solver (standart program to EDA)

Split dataset into Training model:Validation to support model

The dataset is split to **separate model learning from model evaluation**. This prevents information leakage and allows an objective assessment of how well the model generalizes to unseen data, which is critical in credit-risk classification (good vs. bad loans) also based in the Core of the business problem.

The screenshot shows the Analytic Solver Data Science interface. The top menu bar includes File, Home, Insert, Page Layout, Formulas, Data, Review, View, Help, Analytic Solver, and Data Science. The Data Science tab is selected. Below the menu is a toolbar with icons for Model, Get Data, Generate Data, Explore, Transform, Cluster, Text, Partition, ARIMA, Smoothing, Partition, Classify, Predict, Associate, Score, License, and Help. The main workspace is divided into sections: Inputs, Partition Summary, and Partitioned Data. The Inputs section contains tabs for Data, Variables, and Partitioning Parameters. The Data tab shows the workbook is 'Data-Capstone-Project.xlsx', the worksheet is 'data-capstone-project.csv', the range is '\$A\$1:\$S\$7143', and there are 7142 records. The Variables tab lists 17 selected variables: id, member\_id, term, purpose, loan\_status, loan\_amnt, int\_ratef, installment, home\_ownership, ownership\_label, annual\_inc, verification\_status, revol\_bal, revol\_util, total\_acc, and acc\_open\_past\_12\_mths. The Partitioning Parameters tab shows a Partitioning type of RANDOM, Random seed of 12345, and a Ratio - Training of 0.6. The Partition Summary section shows 4285 records for Training and 2857 for Validation. The Partitioned Data section displays a table of 15 records from the 'data-capstone-project.csv' file, including columns for Record ID, id, member\_id, term, purpose, loan\_status, loan\_amnt, int\_ratef, installment, home\_ownership, ownership\_label, annual\_inc, verification\_status, revol\_bal, revol\_util, total\_acc, and acc\_open\_past\_12\_mths. The table rows show various loan details and ownership statuses.

Record ID	id	member_id	term	purpose	loan_status	loan_amnt	int_ratef	installment	home_ownership	ownership_label	annual_inc	verification_status	revol_bal	revol_util	total_acc	acc_open_past_12_mths
Record 1	62286683	66483442	36 months	credit_card	Fully Paid	\$ 24,000	7.9%	\$ 750.86	MORTGAGE		1	\$ 237,500.00	Source Verified	\$ 28,279	36.9%	25
Record 5	42181434	45138158	36 months	credit_card	Fully Paid	\$ 12,600	6.7%	\$ 387.22	OWN		2	\$ 73,800.00	Not Verified	\$ 9,904	20.7%	25
Record 8	65905100	70609838	36 months	credit_card	Fully Paid	\$ 8,000	7.9%	\$ 250.29	OWN		2	\$ 47,840.00	Source Verified	\$ 8,019	46.9%	11
Record 11	53734742	57275484	36 months	credit_card	Charged Off	\$ 10,000	11.0%	\$ 327.34	RENT		0	\$ 36,000.00	Source Verified	\$ 9,022	67.8%	49
Record 12	63364494	67706221	36 months	credit_card	Fully Paid	\$ 10,000	5.3%	\$ 301.15	RENT		0	\$ 110,000.00	Source Verified	\$ 10,412	45.3%	24
Record 15	60376435	64353199	36 months	credit_card	Fully Paid	\$ 34,000	6.2%	\$ 1,038.05	MORTGAGE		1	\$ 250,000.00	Source Verified	\$ 34,729	36.5%	38

## Categorical variables

In this step was convert the categorical variables into categorical predictors creating dummies to able define a valid and unbiased set of predictors for the classifications task into the loan\_status

total_pymnt	loan_status_Charged Off	loan_status_Fully Paid
24,948.45	0	1
13,125.77	0	1
8,351.54	0	1
3,594.63	1	0
10,243.02	0	1
35,278.71	0	1
7,542.84	0	1
7,965.97	0	1
6,850.96	1	0
26,006.83	0	1
6,405.75	0	1
17,467.63	0	1
11,009.02	0	1
15,631.77	0	1
17,566.02	0	1
8,155.32	0	1
18,956.07	0	1
7,954.57	1	0
6,533.91	0	1
7,692.95	0	1
21,508.24	0	1
27,561.73	0	1
28,052.89	0	1
6,315.16	0	1
20,752.22	0	1
6,129.10	0	1
21,032.83	0	1
23,881.36	0	1
9,479.09	0	1
6,276.65	0	1
2,600.42	0	1
1,051.86	1	0
1,643.84	1	0
4,016.34	1	0

## Logistic Regression Model

This is with the objective to classify loans into good and bad loans using logistic regression model,

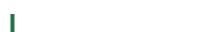
Predictions and probabilities were generated **within the same dataset** using the partition column.

**True Positives (TP):** Bad loans correctly predicted as bad.

**True Negatives (TN):** Good loans correctly predicted as good.

TP and TN were computed using validation rows only.

Model performance was assessed using the **ROC curve and AUC** reported by Analytical solver program where use the loan status created in the partition data (Model training) such dependent variable the **loan\_status** (Core problem) with the explanatory variables excel total\_pymnt



### Validation: Classification Summary

Confusion Matrix			
Actual\Predicted	Charged Off	Fully Paid	
Charged Off	24	437	
Fully Paid	17	2379	

Error Report				
Class	# Cases	# Errors	% Error	
Charged Off	461	437	94.79393	
Fully Paid	2396	17	0.709516	
Overall	2857	454	15.89079	

Metrics	
Metric	Value
Accuracy (#correct)	2403
Accuracy (%correct)	84.10920546
Specificity	0.052060738
Sensitivity (Recall)	0.992904841
Precision	0.844815341
F1 score	0.912893323
Success Class	Fully Paid
Success Probability	0.5

Here able to see the success probability in the portafolio for investment based in the good or bad loans where use

Now will be use the Model Metrics (Validation Perfomance)

To this convert the logistic regression outputs (probabilities) into measurable model quality on Validation data

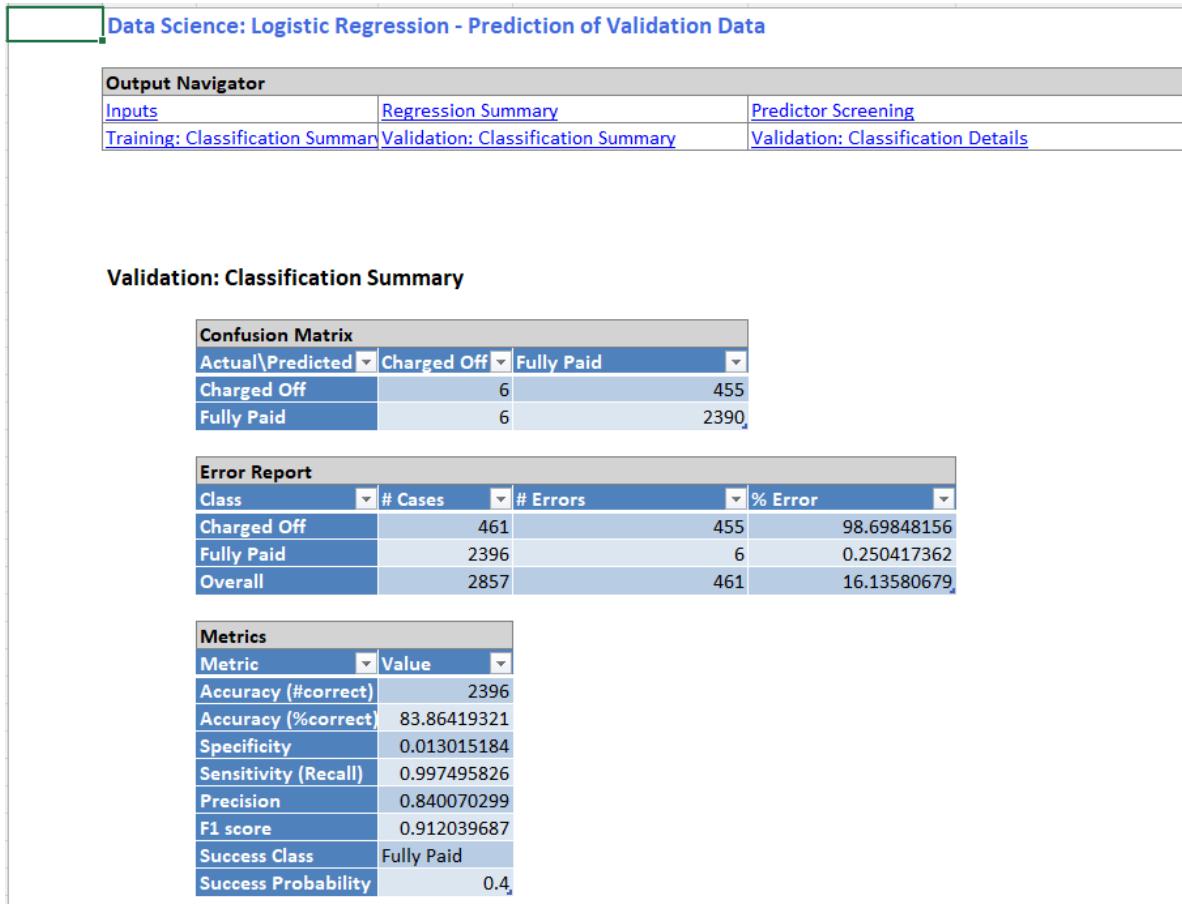
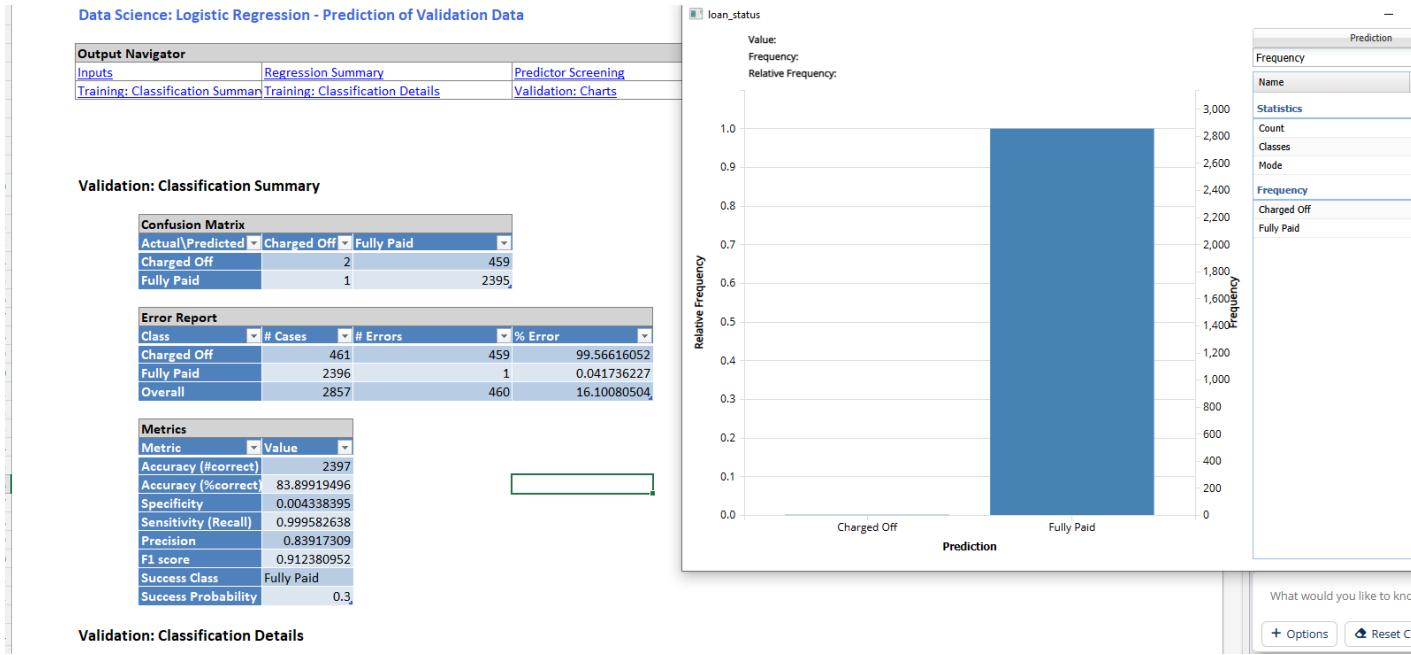
With the Confusion Matrix Counts based in different cutoffs for the necessary validation

#### Validation: Classification Summary

Confusion Matrix		
Actual\Predicted	Charged Off	Fully Paid
Charged Off	55	406
Fully Paid	73	2323

Error Report				
Class	# Cases	# Errors	% Error	
Charged Off	461	406	88.06941432	
Fully Paid	2396	73	3.046744574	
Overall	2857	479	16.76583829	

Metrics	
Metric	Value
Accuracy (#correct)	2378
Accuracy (%correct)	83.23416171
Specificity	0.119305857
Sensitivity (Recall)	0.969532554
Precision	0.851227556
F1 score	0.906536585
Success Class	Fully Paid
Success Probability	0.6



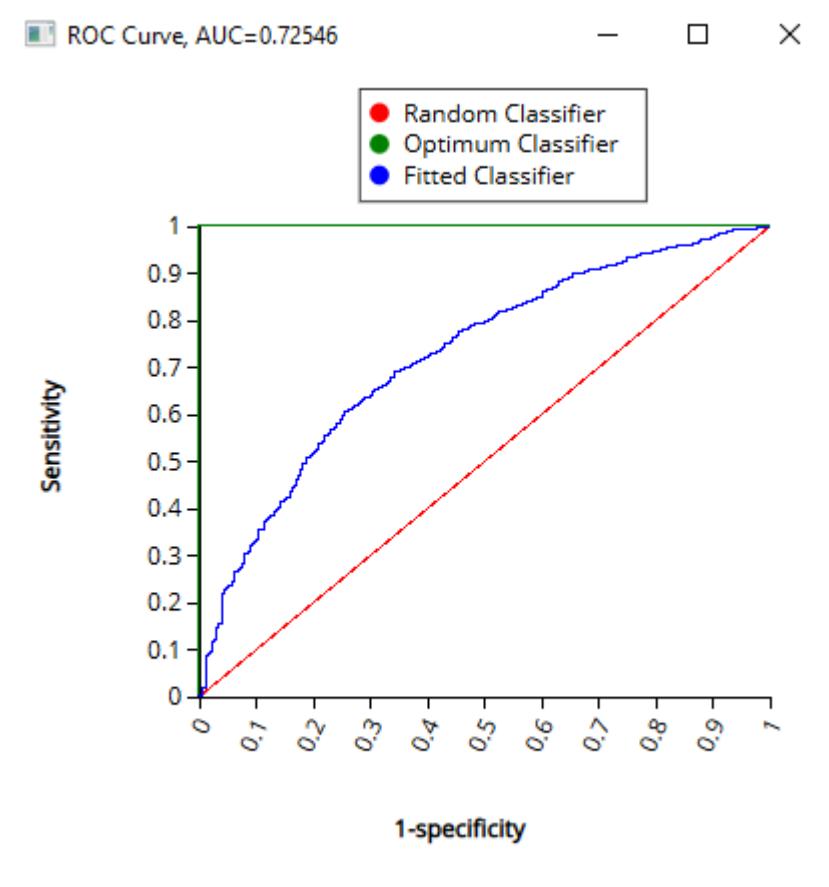
Here was be resumed the cutoffs for the validation and to asses the risk and meet more accuracy to evaluate the logistic regression model beyond a single arbitrary threshold, multiple probability cutoffs were tested using the validation dataset

Cutoff	Default Detected (TP)	Defaults Missed (FN)	False Positives (FP)	Key Behavior
0.3	Very low (2)	Extremely high	Minimal	Extremely permissive; almost all loans classified as Fully Paid
0.4	Very low (6)	Very high	Very low	Slight improvement, but defaults largely undetected
0.5	Moderate (24)	High	Low	Balanced baseline; still conservative toward Fully Paid
0.6	Higher (55)	Lower	Higher	Improved default detection with increased false positives

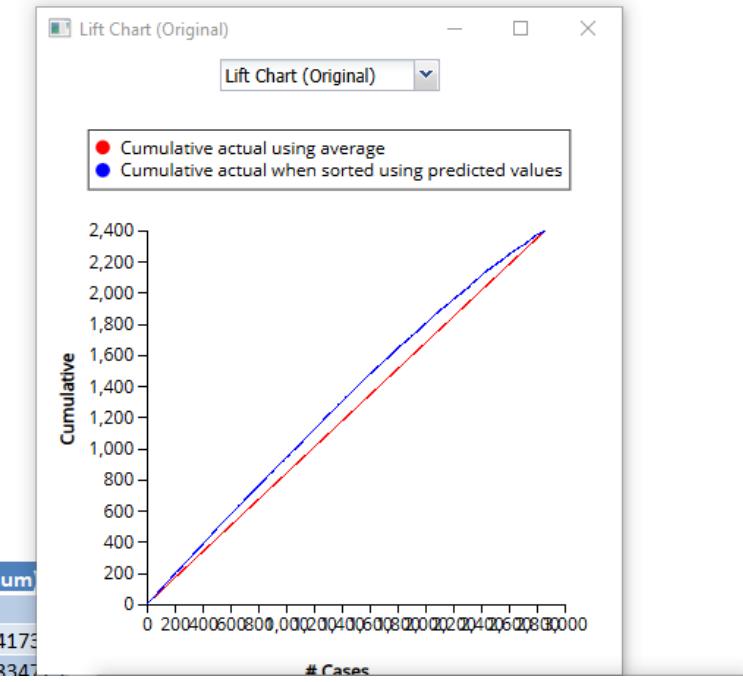
This model consistently identifying Fully Paid loans, as reflected by high recall for the classes

## Step 4 Model Performance

The model was evaluated on unseen validation data using ROC analysis. The area AUC (Area Under the Curve) of 0.725 indicates good discriminatory power between defaulted and non-defaulted loans



Also the lift decile analysis show that loans ranked by predicted probability outperform random selection, especially in the top deciles, validating the use of the model for loan prioritization



And decision to take 0.6 such decision tool based in the probability cutoff were analyzed to understand classification trade-offs. However, cutoffs selection was driven by business risk tolerance rather than statistical optimization alone

cutoff 0.6	cutoff 0.3	
<b>Validation: Classification Summary</b>		
<b>Confusion Matrix</b>		
Actual\	Charged	Fully Pa
Charged	55	406
Fully Paid	73	2323
<b>Validation: Classification Summary</b>		
<b>Confusion Matrix</b>		
Actual\	Charged	Fully Pa
Charged	2	459
Fully Paid	1	2395
<b>Validation: Classification Summary</b>		
<b>Confusion Matrix</b>		
Actual\	Charged	Fully Pa
Charged	24	437
Fully Paid	17	2379

## **Step 5 Decision Framework (Business Answer)**

Turn this model into probabilities into a concrete investment decision in a portfolio where which loan are selected and how much capital is allocated and what risk and return is expected where just now with the validation dataset is able to expect a conservative investor, the priority is to reduce defaults = 0.6 or if want maximize acceptance with controlled risk = 0.5.

In this case the investor choose the option 0.6 to control default risk  
Loans predicted probability of default below this threshold were considered eligible for investment computed as the product of probability of default and loan amount

Where need use the Expected Loss + PD \* Loan\_amnt

To this need create a unique value ID in both dataset (Dataset original (in this case was created a copy from the original for security asses) loan\_amnt) and the (Validation 0.6)

In the original dataset with simple (=ROW) can add a Primary KEY ID

KEYID	id	member	term	purpose	loan_status	Label	Loan	loan_amnt	int_rate	installment	home_ownership	ownership_label	annual_inc	
1	46314315	49422035	36 months	credit_card	Fully Paid	0 \$	8,000	6.7%	\$	245.85	RENT	0 \$	4	
2	51317198	54726945	36 months	credit_card	Fully Paid	0 \$	12,175	9.2%	\$	388.13	MORTGAGE	1 \$	10	
3	42984750	45981489	36 months	credit_card	Charged Off	1 \$	6,400	6.9%	\$	197.38	RENT	0 \$	4	
4	42181434	45138158	36 months	credit_card	Fully Paid	0 \$	12,600	6.7%	\$	387.22	OWN	2 \$	7	
5	38457385	41251256	36 months	credit_card	Fully Paid	0 \$	9,000	8.7%	\$	284.82	MORTGAGE	1 \$	8	
6	61943001	66135720	36 months	credit_card	Fully Paid	0 \$	3,500	8.2%	\$	109.97	MORTGAGE	1 \$	8	
7	65905100	70609838	36 months	credit_card	Fully Paid	0 \$	8,000	7.9%	\$	250.29	OWN	2 \$	4	
8	51256140	54515885	36 months	credit_card	Charged Off	1 \$	6,000	7.9%	\$	187.72	RENT	0 \$	4	
9	55461218	59062933	36 months	credit_card	Fully Paid	0 \$	6,000	8.2%	\$	188.52	RENT	0 \$	5	
10	53734742	57275484	36 months	credit_card	Charged Off	1 \$	10,000	11.0%	\$	327.34	RENT	0 \$	5	
11	63364494	67706221	36 months	credit_card	Fully Paid	0 \$	10,000	5.3%	\$	301.15	RENT	0 \$	13	
12	38658348	41442230	36 months	credit_card	Fully Paid	0 \$	21,000	6.0%	\$	639.15	OWN	2 \$	5	
13	41079352	43955083	36 months	credit_card	Charged Off	1 \$	16,000	18.3%	\$	580.45	RENT	0 \$	6	
15	43955321	46972042	36 months	credit_card	Fully Paid	0 \$	6,800	14.7%	\$	234.57	MORTGAGE	1 \$	5	
16	57713792	61466545	36 months	credit_card	Fully Paid	0 \$	25,000	7.3%	\$	774.91	MORTGAGE	1 \$	12	
17	40962381	43838261	36 months	credit_card	Fully Paid	0 \$	7,500	7.9%	\$	234.65	MORTGAGE	1 \$	5	
20	55545027	59146796	36 months	credit_card	Fully Paid	0 \$	5,600	9.2%	\$	178.53	MORTGAGE	1 \$	13	
21	43420028	46446765	36 months	credit_card	Charged Off	1 \$	12,000	17.6%	\$	431.20	RENT	0 \$	6	
22	43480116	46506869	36 months	credit_card	Fully Paid	0 \$	24,000	9.2%	\$	765.10	RENT	0 \$	8	
23	40363063	43227900	36 months	credit_card	Fully Paid	0 \$	6,000	9.5%	\$	192.17	RENT	0 \$	6	
24	22	66595145	71320993	36 months	credit_card	Fully Paid	0 \$	16,800	7.3%	\$	520.74	MORTGAGE	1 \$	5
25	23	54533710	58114430	36 months	credit_card	Fully Paid	0 \$	10,000	12.7%	\$	335.45	RENT	0 \$	10
26	24	67458304	72270094	36 months	credit_card	Fully Paid	0 \$	15,625	12.0%	\$	518.90	RENT	0 \$	5
27	25	38505940	41299744	36 months	credit_card	Fully Paid	0 \$	16,000	8.2%	\$	502.79	RENT	0 \$	5
28	26	61541044	65659832	36 months	credit_card	Fully Paid	0 \$	10,000	11.5%	\$	329.91	MORTGAGE	1 \$	6
29	27	43529541	46556272	36 months	credit_card	Fully Paid	0 \$	8,000	13.3%	\$	270.83	MORTGAGE	1 \$	5
30	28	40197818	43062555	36 months	credit_card	Fully Paid	0 \$	18,000	12.0%	\$	597.78	MORTGAGE	1 \$	8
32	30	61473698	65592561	36 months	credit_card	Charged Off	1 \$	3,000	15.6%	\$	104.90	RENT	0 \$	2
33	31	40380675	43245399	36 months	credit_card	Charged Off	1 \$	15,000	12.4%	\$	501.02	RENT	0 \$	6
34	32	46809202	49957173	36 months	credit_card	Fully Paid	0 \$	6,000	11.0%	\$	196.41	RENT	0 \$	11
35	33	63246010	67597774	36 months	credit_card	Fully Paid	0 \$	19,200	5.3%	\$	578.21	MORTGAGE	1 \$	13
36	34	39289248	42092966	36 months	credit_card	Fully Paid	0 \$	7,000	12.4%	\$	233.81	MORTGAGE	1 \$	4
37	35	38372414	41156198	36 months	credit_card	Fully Paid	0 \$	16,000	10.5%	\$	519.97	MORTGAGE	1 \$	7
38	36	68434571	73324336	36 months	credit_card	Fully Paid	0 \$	20,000	12.0%	\$	664.20	MORTGAGE	1 \$	6
40	38	58110712	61914445	36 months	credit_card	Fully Paid	0 \$	25,000	11.5%	\$	824.76	RENT	0 \$	12
41	39	56632962	60314707	36 months	credit_card	Fully Paid	0 \$	10,000	13.3%	\$	338.54	MORTGAGE	1 \$	4
42	40	44470689	68336720	36 months	credit_card	Fully Paid	0 \$	24,000	14.7%	\$	917.97	RENT	0 \$	6

On the validation set use the formula (=RIGHT) to arrange the RowKey where each number is in the original dataset

**Validation: Classification Details**

KEYID	Record ID	loan_status	Prediction: loan_st	PostProb: Fully Paid	PostPro
2689	Record 2689	Fully Paid	Fully Paid	0.870499015	0.129501
5353	Record 5353	Fully Paid	Fully Paid	0.921826852	0.078173
1637	Record 1637	Fully Paid	Fully Paid	0.961300438	0.0387
3555	Record 3555	Fully Paid	Fully Paid	0.780806853	0.219193
5151	Record 5151	Charged Off	Fully Paid	0.653485363	0.346515
4246	Record 4246	Fully Paid	Fully Paid	0.863877669	0.136122
5467	Record 5467	Charged Off	Charged Off	0.557777969	0.442222
6372	Record 6372	Charged Off	Fully Paid	0.733939059	0.266061
6980	Record 6980	Fully Paid	Fully Paid	0.848458508	0.151541
3816	Record 3816	Fully Paid	Fully Paid	0.951646477	0.048354
6929	Record 6929	Charged Off	Fully Paid	0.921627799	0.078372
3403	Record 3403	Fully Paid	Fully Paid	0.906068458	0.093932
3326	Record 3326	Fully Paid	Fully Paid	0.888188166	0.111812
2578	Record 2578	Fully Paid	Fully Paid	0.901627846	0.098372
1823	Record 1823	Fully Paid	Fully Paid	0.924439816	0.075556
5806	Record 5806	Fully Paid	Fully Paid	0.92754895	0.072451
2937	Record 2937	Charged Off	Fully Paid	0.613615351	0.386385
7087	Record 7087	Fully Paid	Fully Paid	0.852899869	0.1471
4389	Record 4389	Fully Paid	Fully Paid	0.641825381	0.358175
2798	Record 2798	Fully Paid	Fully Paid	0.988659594	0.01134
6197	Record 6197	Fully Paid	Fully Paid	0.697131746	0.302868
694	Record 694	Fully Paid	Fully Paid	0.691775948	0.308224
6146	Record 6146	Charged Off	Fully Paid	0.828811638	0.171188
2793	Record 2793	Fully Paid	Fully Paid	0.650581601	0.349418
4861	Record 4861	Fully Paid	Fully Paid	0.882669786	0.11733
1789	Record 1789	Charged Off	Fully Paid	0.839489671	0.16051
6625	Record 6625	Charged Off	Charged Off	0.485081958	0.514918
6538	Record 6538	Fully Paid	Fully Paid	0.682105987	0.317894
2584	Record 2584	Fully Paid	Fully Paid	0.783038732	0.216961
2474	Record 2474	Charged Off	Charged Off	0.546165363	0.453835
4642	Record 4642	Fully Paid	Fully Paid	0.868481207	0.131519

Now use JOIN with the **VLOOKUP** or **XLOOKUP** to arrange the specific data to the dataset to run the model in this case I used **VLOOKUP**

=VLOOKUP(A2,Validation\_\_Classification\_Details\_14[#All],6, FALSE)

	M	N	O	P	Q	R	S	T	U	V	W
label	annual_in	Percentile	verification	revol_bal	revol_util	total_acc	acc_open_past	total_pymnt	PD-Default		
102	2 \$ 84,000.00	REMOVE	Source Verifi	\$ 44,411	57.7%	27	4 \$ 7,416.05		0.092863807		
103	2 \$ 65,000.00	REMOVE	Verified	\$ 54,589	89.5%	16	1 \$ 11,524.25		0.557226875		
104	1 \$ 40,000.00	REMOVE	Not Verified	\$ 7,257	36.3%	21	6 \$ 10,230.34		0.087386855		
112	1 \$ 100,000.00	REMOVE	Source Verifi	\$ 46,925	81.5%	21	5 \$ 11,058.23		0.205212471		
117	0 \$ 67,000.00	REMOVE	Verified	\$ 8,569	19.6%	45	18 \$ 6,768.33		0.321611392		
122	1 \$ 85,000.00	REMOVE	Source Verifi	\$ 8,722	46.4%	24	3 \$ 16,339.69		0.085436712		
125	2 \$ 47,000.00	REMOVE	Verified	\$ 10,681	55.1%	29	11 \$ 9,942.83		0.273601922		
127	0 \$ 45,000.00	REMOVE	Not Verified	\$ 24,538	47.4%	17	3 \$ 7,247.59		0.1064399		
128	1 \$ 30,000.00	REMOVE	Source Verifi	\$ 9,953	38.7%	39	7 \$ 11,314.45		0.182722523		
132	0 \$ 60,000.00	REMOVE	Source Verifi	\$ 5,627	25.8%	56	4 \$ 8,039.73		0.143779015		
136	2 \$ 95,000.00	REMOVE	Source Verifi	\$ 39,420	63.5%	43	2 \$ 7,802.82		0.095019587		
138	1 \$ 53,000.00	REMOVE	Not Verified	\$ 17,707	28.2%	37	12 \$ 14,027.66		0.123602948		
139	1 \$ 77,000.00	REMOVE	Source Verifi	\$ 30,869	71.1%	30	4 \$ 15,934.28		0.086659582		
140	1 \$ 95,000.00	REMOVE	Not Verified	\$ 4,638	53.3%	38	5 \$ 10,510.09		0.076282982		
141	1 \$ 129,000.00	REMOVE	Verified	\$ 73,793	35.0%	67	8 \$ 28,872.20		0.044842465		
145	1 \$ 90,000.00	REMOVE	Source Verifi	\$ 23,268	71.6%	22	3 \$ 35,037.49		0.163096976		
148	0 \$ 30,000.00	REMOVE	Not Verified	\$ 12,112	44.0%	11	6 \$ 10,504.87		0.283976986		
150	1 \$ 84,000.00	REMOVE	Source Verifi	\$ 15,236	39.8%	43	10 \$ 15,622.74		0.065915349		
152	1 \$ 50,000.00	REMOVE	Source Verifi	\$ 8,458	34.1%	22	7 \$ 15,661.94		0.088752508		
153	1 \$ 169,900.00	REMOVE	Not Verified	\$ 11,989	54.2%	57	9 \$ 13,635.76		0.04319477		
156	2 \$ 47,000.00	REMOVE	Not Verified	\$ 19,273	47.8%	32	3 \$ 12,615.36		0.103612278		
161	2 \$ 110,500.00	REMOVE	Source Verifi	\$ 26,535	32.4%	38	11 \$ 20,510.37		0.086446188		
163	2 \$ 42,804.00	REMOVE	Source Verifi	\$ 16,330	39.2%	30	9 \$ 7,288.52		0.197904077		
166	2 \$ 22,000.00	REMOVE	Verified	\$ 18,015	79.0%	10	1 \$ 11,255.18		0.482632198		
171	1 \$ 140,000.00	REMOVE	Source Verifi	\$ 35,967	61.7%	38	5 \$ 30,139.59		0.053154758		
173	0 \$ 28,000.00	REMOVE	Not Verified	\$ 10,254	39.6%	14	5 \$ 8,003.56		0.217589104		
174	2 \$ 82,000.00	REMOVE	Not Verified	\$ 16,820	19.4%	30	10 \$ 20,474.16		0.135855067		
176	1 \$ 120,000.00	REMOVE	Source Verifi	\$ 34,876	48.4%	39	10 \$ 26,804.89		0.073102527		
177	2 \$ 95,000.00	REMOVE	Source Verifi	\$ 11,302	38.8%	27	3 \$ 22,281.69		0.063433968		
178	1 \$ 85,000.00	REMOVE	Not Verified	\$ 6,102	55.0%	21	5 \$ 6,641.92		0.118408794		
179	0 \$ 40,000.00	REMOVE	Source Verifi	\$ 14,557	54.5%	36	2 \$ 15,012.76		0.157328487		
181	1 \$ 65,000.00	REMOVE	Source Verifi	\$ 15,724	80.6%	23	7 \$ 9,499.65		0.145881855		
184	2 \$ 43,000.00	REMOVE	Not Verified	\$ 4,095	59.3%	18	1 \$ 11,081.40		0.20820942		
192	1 \$ 40,000.00	REMOVE	Source Verifi	\$ 5,122	41.0%	37	9 \$ 7,784.86		0.158892838		
195	0 \$ 69,000.00	REMOVE	Source Verifi	\$ 9,414	42.6%	20	3 \$ 11,274.56		0.09913113		
198	0 \$ 47,200.00	REMOVE	Not Verified	\$ 4,350	48.4%	23	6 \$ 3,288.40		0.139380505		
199	1 \$ 126,000.00	REMOVE	Source Verifi	\$ 57,311	61.7%	34	2 \$ 31,150.62		0.05175746		

Next step is find the better portafolio for Business answer

With the next formula

$$\text{Expected Loss} = \text{PD} * \text{Loan\_amnt}$$

acc_open_past	total_pymnt	PD-Default	Expected_Loss	Elegible
3	\$ 6,933.65	0.079627279	\$ 477.76	Yes
4	\$ 11,593.05	0.156883919	\$ 1,600.22	Yes
7	\$ 22,398.21	0.130148901	\$ 2,733.13	Yes
9	\$ 8,866.60	0.058522067	\$ 453.55	Yes
2	\$ 1,669.03	0.138626131	\$ 207.94	Yes
12	\$ 2,187.25	0.181273879	\$ 362.55	Yes
7	\$ 2,211.77	0.12156219	\$ 267.44	Yes
1	\$ 1,073.43	0.481166732	\$ 481.17	Yes
4	\$ 6,166.16	0.050057071	\$ 300.34	Yes
7	\$ 8,242.11	0.055269768	\$ 382.74	Yes
7	\$ 3,145.20	0.136533989	\$ 382.30	Yes
9	\$ 2,108.49	0.055666371	\$ 111.33	Yes
9	\$ 511.43	0.376936018	\$ 565.40	Yes
5	\$ 1,861.80	0.026951711	\$ 48.51	Yes
6	\$ 1,069.51	0.147747161	\$ 443.24	Yes
3	\$ 37,608.02	0.044396378	\$ 1,553.87	Yes
7	\$ 2,058.50	0.266405531	\$ 479.53	Yes
5	\$ 2,238.09	0.179712762	\$ 345.95	Yes
8	\$ 1,522.37	0.085942606	\$ 128.91	Yes
11	\$ 1,060.33	0.19855358	\$ 198.55	Yes
3	\$ 1,008.56	0.089511186	\$ 89.51	Yes
7	\$ 404.78	0.023876869	\$ 47.75	Yes
6	\$ 595.24	0.070000537	\$ 210.00	Yes
5	\$ 5,782.20	0.094159993	\$ 470.80	Yes
2	\$ 8,927.61	0.224867847	\$ 1,911.38	Yes
3	\$ 10,415.74	0.163074391	\$ 1,598.13	Yes
1	\$ 3,717.79	0.088849791	\$ 310.97	Yes
2	\$ 5,507.21	0.130483733	\$ 652.42	Yes
7	\$ 4,748.16	0.181896649	\$ 818.53	Yes
5	\$ 4,120.57	0.274748558	\$ 1,098.99	Yes
3	\$ 4,056.51	0.063836657	\$ 255.35	Yes
7	\$ 5,222.25	0.125117488	\$ 625.59	Yes
0	\$ 5,496.73	0.534897109	\$ 2,674.49	Yes
5	\$ 7,433.12	0.100617966	\$ 654.02	Yes
4	\$ 962.60	0.122324954	\$ 244.65	Yes
9	\$ 3,018.39	0.031307514	\$ 93.92	Yes
8	\$ 5,016.56	0.16747764	\$ 937.30	No

ta-loan

Validation.06

STDPartition

Validation0.3 ...

⊕

⋮

&lt;

Additionally add filter to see only the Elegible Loans for the investor

## Step 6 Consolidation Portfolio for Investor

Now need build the portafolio for the investor at only elegible loans

Using Sum and logical functions

	verificatio	revol_bal	revol_util	total_acc	acc_open_past_	total_pymnt	PD-Default	Expected_Loss	Eligible	Cum_Investment	Selected
4	Source Verifi	\$ 10,908		74.2%	19	6 \$ 15,357.69	0.079627279	\$ 1,194.41	Yes	\$ 15,000	1
5	Not Verified	\$ 9,272		74.2%	27	4 \$ 10,172.41	0.156883919	\$ 1,490.40	Yes	\$ 24,500	1
7	Not Verified	\$ 10,561		76.5%	7	0 \$ 9,707.42	0.130148901	\$ 1,145.31	Yes	\$ 45,900	1
8	Verified	\$ 9,213		8.4%	31	11 \$ 2,215.66	0.058522067	\$ 117.04	Yes	\$ 47,900	1
0	Not Verified	\$ 22,193		83.4%	10	4 \$ 9,346.68	0.138626131	\$ 1,247.64	Yes	\$ 64,900	1
1	Not Verified	\$ 10,032		46.7%	69	7 \$ 13,230.59	0.181273879	\$ 2,175.29	Yes	\$ 76,900	1
4	Source Verifi	\$ 91,165		66.6%	34	4 \$ 1,902.73	0.12156219	\$ 203.62	Yes	\$ 98,575	1
5	Source Verifi	\$ 7,108		64.6%	7	3 \$ 5,512.52	0.48116732	\$ 2,405.83	Yes	\$ 103,575	1
8	Not Verified	\$ 889		2.8%	28	1 \$ 2,150.34	0.050057071	\$ 100.11	Yes	\$ 146,375	1
10	Verified	\$ 3,749		50.0%	12	3 \$ 1,008.56	0.055269768	\$ 55.27	Yes	\$ 154,875	1
18	Not Verified	\$ 14,804		68.2%	23	3 \$ 2,022.32	0.136533989	\$ 273.07	Yes	\$ 257,300	1
11	Source Verifi	\$ 6,674		42.8%	27	5 \$ 5,471.19	0.055666371	\$ 278.33	Yes	\$ 288,300	1
12	Not Verified	\$ 13,726		48.8%	26	7 \$ 2,058.50	0.376936018	\$ 678.48	Yes	\$ 290,100	1
15	Verified	\$ 1,213		10.5%	45	11 \$ 1,060.33	0.026951711	\$ 26.95	Yes	\$ 312,100	1
17	Verified	\$ 17,797		73.8%	10	3 \$ 4,461.43	0.147747161	\$ 590.99	Yes	\$ 323,100	1
19	Not Verified	\$ 6,091		88.3%	38	7 \$ 2,327.39	0.044396378	\$ 93.23	Yes	\$ 345,200	1
11	Verified	\$ 7,547		64.5%	24	12 \$ 3,296.73	0.266405531	\$ 799.22	Yes	\$ 373,200	1
14	Verified	\$ 5,748		58.1%	17	12 \$ 2,187.25	0.179712762	\$ 359.43	Yes	\$ 404,800	1
15	Source Verifi	\$ 7,693		90.5%	18	4 \$ 9,409.34	0.085942606	\$ 730.51	Yes	\$ 413,300	1
17	Source Verifi	\$ 3,895		34.2%	19	5 \$ 1,861.80	0.19853538	\$ 357.40	Yes	\$ 434,100	1
12	Source Verifi	\$ 5,285		43.7%	14	3 \$ 965.80	0.089511186	\$ 322.24	Yes	\$ 494,700	1
13	Verified	\$ 7,593		17.5%	62	13 \$ 6,439.11	0.023876869	\$ 143.26	Yes	\$ 500,700	1
19	Verified	\$ 5,028		14.0%	29	9 \$ 5,824.08	0.070000537	\$ 392.00	Yes	\$ 531,325	1
14	Source Verifi	\$ 4,477		32.4%	9	2 \$ 1,669.03	0.094159993	\$ 141.24	Yes	\$ 598,700	1
15	Verified	\$ 10,681		55.1%	29	11 \$ 9,942.83	0.224867847	\$ 2,023.81	Yes	\$ 607,700	1
18	Source Verifi	\$ 19,528		32.9%	30	13 \$ 10,662.40	0.163074391	\$ 1,630.74	Yes	\$ 627,700	1
10	Source Verifi	\$ 5,786		24.3%	21	7 \$ 5,222.25	0.088849791	\$ 444.25	Yes	\$ 667,700	1
13	Source Verifi	\$ 80,028		77.6%	34	9 \$ 342.38	0.130483733	\$ 521.93	Yes	\$ 680,900	1
15	Not Verified	\$ 36,761		67.5%	36	3 \$ 1,214.62	0.181896649	\$ 545.69	Yes	\$ 695,900	1
16	Not Verified	\$ 6,910		50.4%	26	9 \$ 511.43	0.274748558	\$ 412.12	Yes	\$ 697,400	1
10	Not Verified	\$ 1,274		7.9%	11	5 \$ 3,236.31	0.063936657	\$ 201.09	Yes	\$ 718,875	1
16	Not Verified	\$ 6,819		17.0%	47	7 \$ 2,226.10	0.125117488	\$ 275.26	Yes	\$ 783,075	1
17	Not Verified	\$ 7,914		60.0%	19	4 \$ 1,105.12	0.534897109	\$ 1,069.79	Yes	\$ 785,075	1
18	Not Verified	\$ 4,737		48.3%	13	3 \$ 2,898.01	0.100617966	\$ 261.61	Yes	\$ 787,675	1
11	Not Verified	\$ 3,830		7.5%	28	6 \$ 2,556.32	0.122324954	\$ 305.81	Yes	\$ 819,175	1
14	Not Verified	\$ 6,384		7.2%	21	5 \$ 6,333.73	0.031307514	\$ 187.85	Yes	\$ 858,800	1
15	Source Verifi	\$ 32,941		50.2%	27	9 \$ 1,582.73	0.167477646	\$ 251.22	Yes	\$ 860,300	1

Once elegible loans were identified and ranked by expected loss, a cumulative investment approach was applied to construct final portfolio under a fixed capital constraint for each elegible loan where 1 is loans included in portfolio and 0 excluded

Where this model is based default risk estimates and expected monetary loss per loan and fixed investment budget of 10M the resulting is the risk elegibility rule

## **Where have this Portfolio performance Summary**

Due to discrete loan sizes, the final portfolio slightly exceeds the target capital constraint, can fixed with a 2 filters but for this capstone the investor take the portfolio

By combining predictive modeling, probability cutoffs, and capital constraints, the analysis moves from model performance to a concrete investment recommendation. The resulting portfolio demonstrates how data-driven decision-making can be applied to lending scenarios to balance risk and return in monetary terms.

## FROM RISK TO RETURN

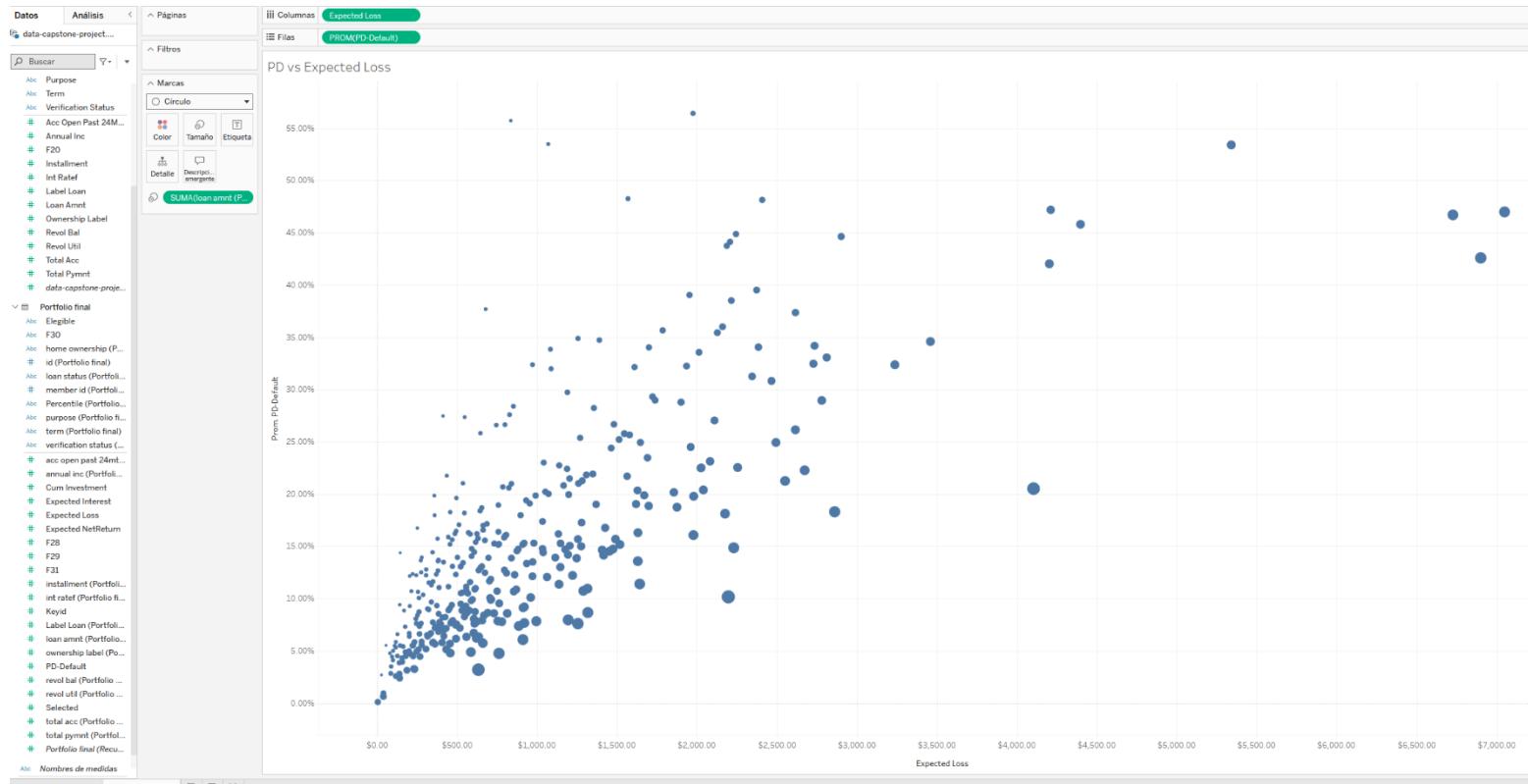
While probability of default and expected loss quantify downside risk, investment decision requires an estimate of expected return. To translate model outputs into an economic decision framework a proxy was constructed loan level.

	Expected_Interest	Expected_NetReturn
L \$	786.6	\$ (193.15)
L \$	266.0	\$ (143.56)
L \$	933.1	\$ (1.66)
L \$	1,919.5	\$ 277.80
L \$	981.6	\$ 95.86
L \$	266.0	\$ (492.93)
L \$	409.5	\$ (489.05)
L \$	549.1	\$ (382.24)
L \$	549.5	\$ (1,234.07)
L \$	568.1	\$ (404.56)
L \$	880.3	\$ 126.09
L \$	200.4	\$ (138.70)
L \$	383.0	\$ 118.43
L \$	1,229.0	\$ (2,230.56)
L \$	1,766.9	\$ (428.92)
L \$	694.3	\$ (367.66)
L \$	383.0	\$ (1,179.92)
L \$	839.4	\$ 571.43
L \$	1,269.0	\$ (605.73)
L \$	1,639.2	\$ 9.20
L \$	617.1	\$ (658.48)
L \$	288.3	\$ (357.42)
L \$	757.4	\$ (649.39)
L \$	278.1	\$ (809.47)
L \$	405.6	\$ (2,496.05)
L \$	1,729.5	\$ (500.13)
L \$	999.0	\$ (4,341.61)
L \$	479.4	\$ (188.22)
L \$	886.3	\$ 46.83
L \$	573.3	\$ 167.38
L \$	778.8	\$ (1,894.14)
	\$ 237,479.52	\$ (125,606.62)

The resulting expected net return is conservative by design, reflecting a risk-controlled investment strategy and the use of simplified return proxies rather than full cash flow modeling

Now will be explain with Visualization for better understanding using Tableau

## PD vs Expected Loss



Scatter plot illustrates the relationship between the predicted probability of default (PD) and the expected loss for individual loans.

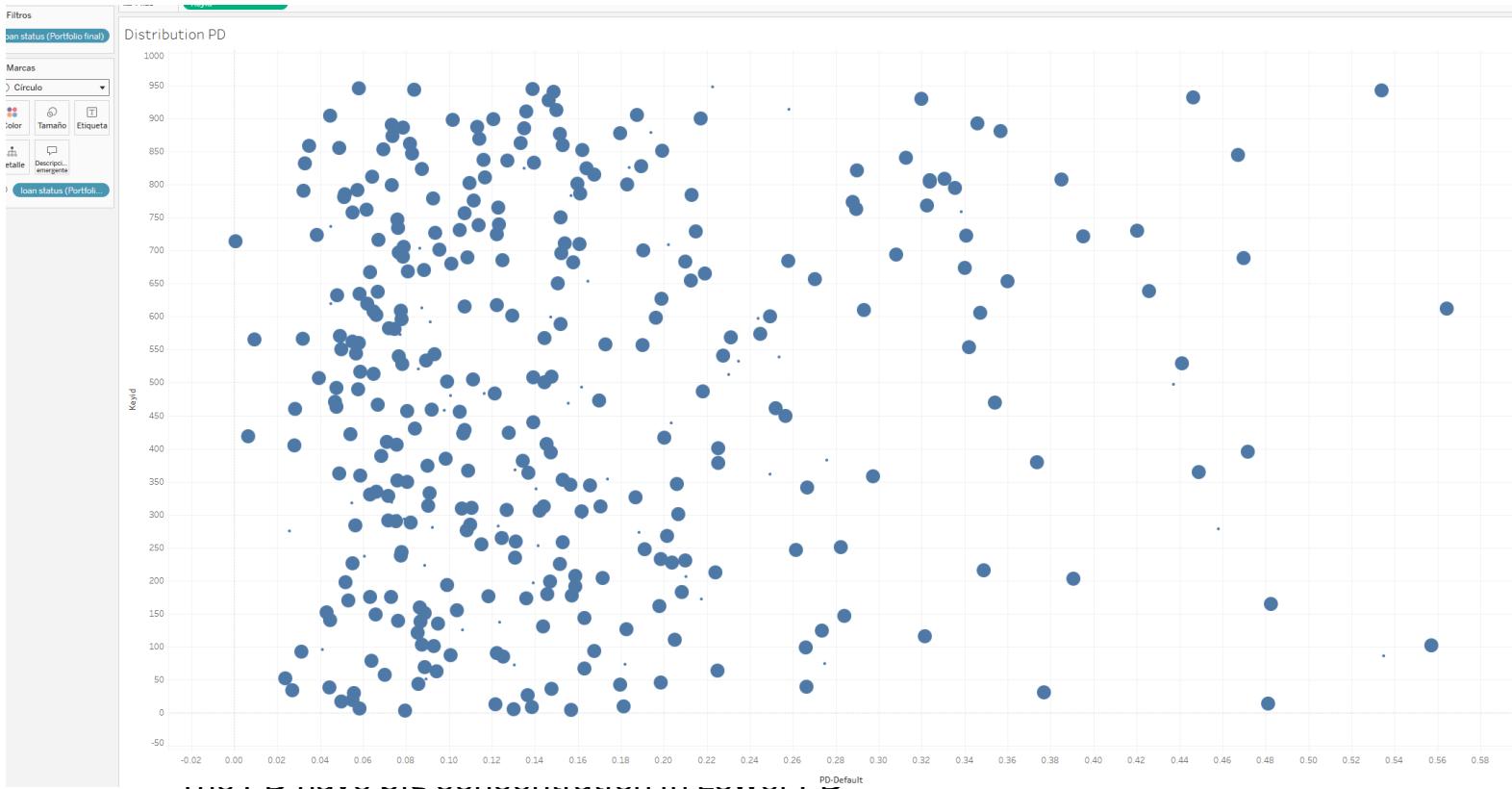
As expected, higher probabilities of default are associated with higher expected losses, reflecting the direct dependency between risk estimates and potential downside exposure.

The dispersion of points highlights heterogeneity in loan sizes, showing that loans with similar default probabilities can still carry very different loss magnitudes depending on the loan amount.

## Distribution of Probability of Default

This scatter plot shows the distribution of predicted probabilities of default across the loan population.

The loans is concentrated at lower PD values, while a smaller number of loans exhibit significantly higher default risk.

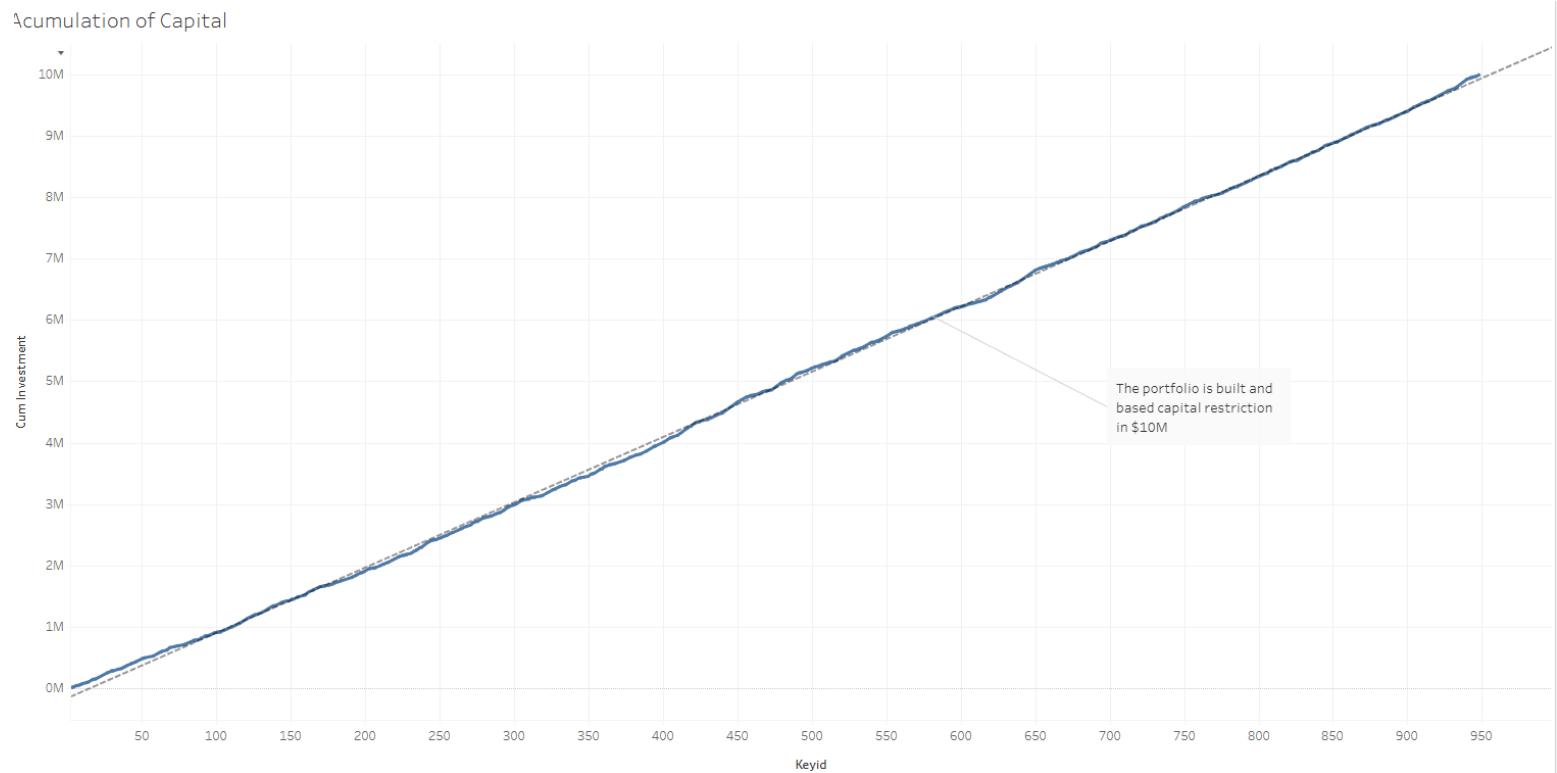


## Accumulation of Capital

The cumulative investment amount as loans are sequentially added according to the portfolio ranking criteria.

The upward trajectory reflects the mechanical accumulation of loan amounts when ordered by risk-adjusted priority.

While the cumulative curve approaches the \$10M capital threshold, the final portfolio selection enforces a strict investment constraint, excluding loans that would breach the limit due to discrete loan sizes.



## KPI BOX

A	B	C	D
Selected	1		
Row Labels	Count of KEYID	Average of PD-Default	Sum of Expected_Loss
credit_card	377	15.58%	\$ 363,086.14
MORTGAGE	144	15.39%	\$ 145,057.93
OWN	50	17.40%	\$ 59,806.55
RENT	183	15.22%	\$ 158,221.67
<b>Grand Total</b>	<b>377</b>	<b>15.58%</b>	<b>\$ 363,086.14</b>

The final investment portfolio was evaluated using a concise set of key performance indicators that summarize capital deployment, risk exposure and expected economic impact, the EL was calculated a 100% Loss given default due to the absence of recovery or collateral data as a result overstate realized losses Although a total capital budget of 10M was available, only 2.4M was deployed. This reflects a **risk-controlled investment strategy**, where the capital was not forcibly allocated when loans exceeded acceptable risk thresholds or would breach the capital constraint due to discrete loan sizes, These KPIs provide a transparent and economically grounded summary of the final portfolio enabling decision-making

Finally, this project demonstrates how predictive analysis can be operationalized into a disciplined investment decision framework a logistic regression model was used to estimate the probability of default loans and was rigorously evaluated on validation data, achieving an AUC of 0.725, indicating solid discriminatory power. Under a fixed capital constraint of 10M, a cumulative investment approach was applied to an eligible loan ranked by expected loss. Due to conservative risk thresholds, discrete loan sizes and a strict enforcement of the capital constraint, the final deploy 2.4M this outcome reflect disciplined risk control rather than forced capital allocation, as resulting in portfolio controlled average default risk and transparent expected downside exposure, with expected losses intentionally overstated due to a 100% loss given-default assumption in the absence of recovery data.