How ACCURATE can I make it?

Predicting Default Risk in Loans

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Problem

When credit card customers default...

- Banks lose revenue
- Fewer loans get approved
- Collections drain staff time & legal resources
- Mispriced credit raises rates for everyone
- Undermine banks' trust

Predicting who'll default can prevent losses!

Dataset

	id	x1	x2	x3	x4	x5	x6	x7	x8	x9	...	x15	x16	x17	x18	x19	x20	x21	x22	x23	y
0	1.0	20000.0	2.0	2.0	1.0	24.0	2.0	2.0	-1.0	-1.0	...	0.0	0.0	0.0	0.0	689.0	0.0	0.0	0.0	0.0	1
1	2.0	120000.0	2.0	2.0	2.0	26.0	-1.0	2.0	0.0	0.0	...	3272.0	3455.0	3261.0	0.0	1000.0	1000.0	1000.0	0.0	2000.0	1
2	3.0	90000.0	2.0	2.0	2.0	34.0	0.0	0.0	0.0	0.0	...	14331.0	14948.0	15549.0	1518.0	1500.0	1000.0	1000.0	1000.0	5000.0	0
3	4.0	50000.0	2.0	2.0	1.0	37.0	0.0	0.0	0.0	0.0	...	28314.0	28959.0	29547.0	2000.0	2019.0	1200.0	1100.0	1069.0	1000.0	0
4	5.0	50000.0	1.0	2.0	1.0	57.0	-1.0	0.0	-1.0	0.0	...	20940.0	19146.0	19131.0	2000.0	36681.0	10000.0	9000.0	689.0	679.0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
29995	29996.0	220000.0	1.0	3.0	1.0	39.0	0.0	0.0	0.0	0.0	...	88004.0	31237.0	15980.0	8500.0	20000.0	5003.0	3047.0	5000.0	1000.0	0
29996	29997.0	150000.0	1.0	3.0	2.0	43.0	-1.0	-1.0	-1.0	-1.0	...	8979.0	5190.0	0.0	1837.0	3526.0	8998.0	129.0	0.0	0.0	0
29997	29998.0	30000.0	1.0	2.0	2.0	37.0	4.0	3.0	2.0	-1.0	...	20878.0	20582.0	19357.0	0.0	0.0	22000.0	4200.0	2000.0	3100.0	1
29998	29999.0	80000.0	1.0	3.0	1.0	41.0	1.0	-1.0	0.0	0.0	...	52774.0	11855.0	48944.0	85900.0	3409.0	1178.0	1926.0	52964.0	1804.0	1
29999	30000.0	50000.0	1.0	2.0	1.0	46.0	0.0	0.0	0.0	0.0	...	36535.0	32428.0	15313.0	2078.0	1800.0	1430.0	1000.0	1000.0	1000.0	1

30000 rows × 25 columns

- n = 30k loans, 22% charge-off rate” (I. Yeh, Che-hui Lien. 2009)
- UCI Default of Credit Card Clients
  - Original Source

- Renamed columns
  - according to source guide
- Key features:
  - numeric: limit_balance, age, bill_amt1–6, pay_amt1–6
  - categorical: sex, education_level, marital_status, repayment_status (PAY_0–PAY_6), default_next_month (target)

CATCH

catches 6 of 10 defaulters

Recall(0): 0.59

TRUE

half of flags come true

Precision(0): 0.51

SAFE

only 12% false flags

Precision(1): 0.88

here's how...

Journey

From one model to the next...

01

Log. Regression

Spaghetti Throwing– trying to see what sticks

02

Random Forest

Could fit non-linear features (limit_bal, late_trend, etc)

04

SVM

Kernels would handle bill/payment splits

03

XGBoost

Handles complex pay/bill interactions – best thus far

Journey

XGB turned out best... now how can I improve it?

05

Features (XGB)

Engineered five features to increase accuracy

06

Tuned (XGB)

grid-searched to tighten fit

07

Balancing (XGB)

Pivoted to balancing, oversampled minority class to lift recall

08

Calibrating (XGB)

Align probability scores, set F1-max cutoff

01 Logistic Regression

(80/20 split, x: all except default, y: default)

	precision	recall	f1-score	support
0	0.82	0.97	0.89	4673
1	0.69	0.24	0.36	1327
accuracy			0.81	6000
macro avg	0.75	0.61	0.62	6000
weighted avg	0.79	0.81	0.77	6000

Thought Process:

Logistic Regression:
– Handles binary classification directly
– Works well with numeric-heavy data
– First model: just throwing something out

Performance?

– Precision on defaulters: 0.51
– Recall: 0.59 F1: 0.55
– Still likely underfitting complex patterns
– No handling of class imbalance or interactions yet

02 Random Forest

(80/20 split, x: all except default, y: default)

	precision	recall	f1-score	support
0	0.83	0.95	0.89	4673
1	0.65	0.33	0.44	1327
accuracy			0.81	6000
macro avg	0.74	0.64	0.66	6000
weighted avg	0.80	0.81	0.79	6000

Thought Process:

Random Forest:
– Handles non-linear features better
– Uses ensemble power to reduce overfitting
– Balances class weight to address imbalance
– Goal: Catch more true defaulters than logistic reg

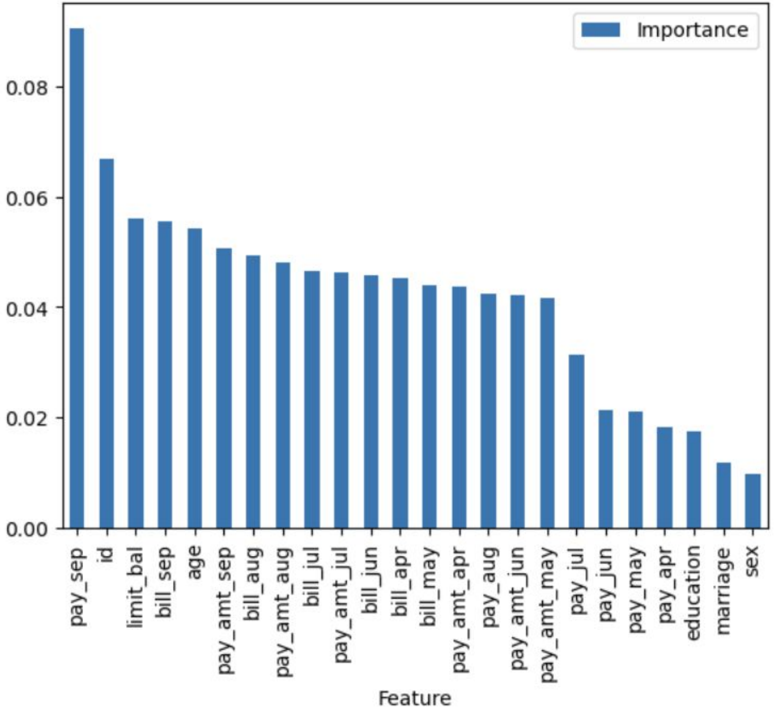
Performance?

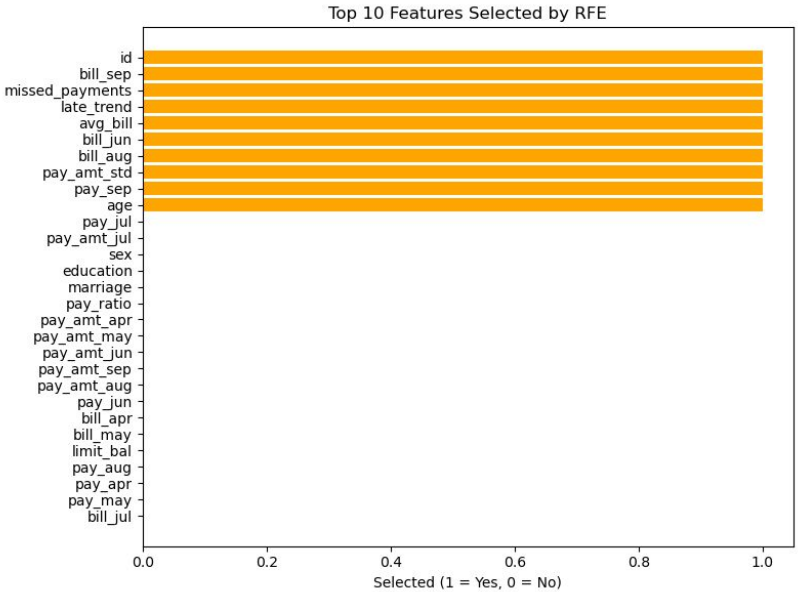
– Precision on defaulters: 0.65
Recall: 0.33   F1: 0.44
– Better once it does flag a defaulter
– Still misses ~67% of them
– Small step forward, but still cautious

Found 10 most predictive features using RF importances

- wanted to understand what signals model relied on
- hoped to reduce noise

=> top 10 = ['id', 'bill_aug', 'pay_amt_sep', 'bill_apr', 'bill_may', 'bill_jun', 'bill_jul', 'bill_sep', 'pay_sep', 'age']





02 Random Forest v2

(80/20 split, x: top 10 (from prev. page), y: default)

	precision	recall	f1-score	support
0	0.83	0.95	0.89	4673
1	0.64	0.34	0.44	1327
accuracy			0.81	6000
macro avg	0.74	0.64	0.67	6000
weighted avg	0.79	0.81	0.79	6000

ROC AUC: 0.76

Thought Process:

Random Forest v2:
– Cut model complexity by using just top 10 features
– Chose based on RF importances + RFE
– Hoped to retain signal while reducing noise + boosting clarity

Performance?

– Precision on defaulters: 0.64
Recall: 0.34 F1: 0.44
– Nearly identical to full-feature RF
– Inch of improvement recall: 0.33 → 0.34
– Simplified model without major loss
– Should be able to use these features for future models

03 SVM

(80/20 split, x: top 10 , y: default)

Thought Process:

SVM:
– Tried a boundary-based model (SVM) to flag risk patterns more decisively
– Used same top 10 features for fairness
– Hoped to push recall much higher, even at cost of precision

	precision	recall	f1-score	support
0	0.88	0.30	0.45	4673
1	0.26	0.86	0.40	1327
accuracy			0.42	6000
macro avg	0.57	0.58	0.42	6000
weighted avg	0.74	0.42	0.43	6000

Performance?

– Precision on defaulters: 0.26 Recall: 0.86   F1: 0.40
– Huge recall jump (↑ from 0.34), barely misses any defaulters
– But 74% of defaulter flags are false alarms
– Overall accuracy: 42%
– Likely overfit to risky cases — tries too hard to catch them all
– Possibly:

- RBF kernel overreacts to patterns in small feature space
- Class_weight = ‘balanced’ + nonlinear boundary = extreme shifts
- Lack of calibration makes it trigger-happy

Massive trade-off: SVM aggressively flags defaulters (high recall), but sacrifices overall accuracy and precision.

04 XGBoost

(80/20 split, x: top 10, y: default)

	precision	recall	f1-score	support
0	0.87	0.83	0.85	4673
1	0.49	0.58	0.53	1327
accuracy			0.77	6000
macro avg	0.68	0.70	0.69	6000
weighted avg	0.79	0.77	0.78	6000

Thought Process:

– Tried XGBoost to better capture nonlinear patterns
– Set scale_pos_weight to help with imbalance
– Wanted a model that could balance recall + precision with more nuance than SVM or RF

Performance?

– Precision on defaulters: 0.49
Recall: 0.58 F1: 0.53
– Most balanced model so far
– Catches a solid % of defaulters (↑ recall vs RF)
– Accuracy = 77% despite fewer features
– Likely benefiting from boosting: iteratively learning where others fail
– May underperform if more interaction terms or deeper features are needed

04 XGBoost v2

+ tuning (randomized)

	precision	recall	f1-score	support
0	0.87	0.83	0.85	4673
1	0.49	0.57	0.53	1327
accuracy			0.77	6000
macro avg	0.68	0.70	0.69	6000
weighted avg	0.79	0.77	0.78	6000

Thought Process:

Hypertuning might help:
– Tried RandomizedSearchCV and Optuna to push performance further
– Targeted f1-score and class balance using scale_pos_weight
– Hoped to reduce false positives without sacrificing recall

Attempt 1:
Parameters tuned:
– n_estimators: [100, 200, 300, 400]
– max_depth: [3, 4, 5, 6, 7]
– learning_rate: [0.01, 0.05, 0.1, 0.2]
– subsample: [0.6, 0.8, 1.0]
– colsample_bytree: [0.6, 0.8, 1.0]
– gamma: [0, 1, 5]

Why / Hope:
– Start with basic knobs
– Aim: catch more defaulters while reducing false positives
– Expected a bump in F1 by balancing fit depth and learning rate

04 XGBoost v3

+ tuning w/ broader search

	precision	recall	f1-score	support
0	0.87	0.84	0.85	4673
1	0.49	0.55	0.52	1327
accuracy			0.78	6000
macro avg	0.68	0.69	0.69	6000
weighted avg	0.79	0.78	0.78	6000

Thought Process:

Broadened search (50 trials)

Attempt 2:

Extra parameters added:

– min_child_weight: [1, 5, 10]

– reg_alpha: [0, 0.1, 1]

– reg_lambda: [0.1, 1, 5]

– Slightly broader ranges for existing params

– learning_rate: [0.001, 0.01, 0.05, 0.1, 0.2]

– n_estimators: [100, 200, 300, 500]

– max_depth: [3, 5, 7, 9]

Why / Hope:

– Try regularization to prevent overfitting

– Add flexibility in tree shape and depth

– See if interaction of new knobs would uncover better balance

04 XGBoost v4

+ tighter tuning

	precision	recall	f1-score	support
0	0.87	0.84	0.86	4673
1	0.50	0.57	0.53	1327
accuracy			0.78	6000
macro avg	0.69	0.71	0.69	6000
weighted avg	0.79	0.78	0.78	6000

Performance?

After three tuning attempts:

– Precision: 0.50 Recall: 0.57 F1: 0.53 (unchanged)

– Nearly identical to untuned XGB; accuracy plateaued at 78%

=> Takeaway: Tuning's juice has been squeezed— time to move on

Thought Process:

Attempt 3:

(All previous params with tighter float sampling)

– learning_rate: 0.0096

– gamma: 4.15

– min_child_weight: 8

– reg_alpha: 0.40

– reg_lambda: 1.04

– n_estimators: 435

– colsample_bytree: 0.80, subsample: 0.80

Why / Hope:

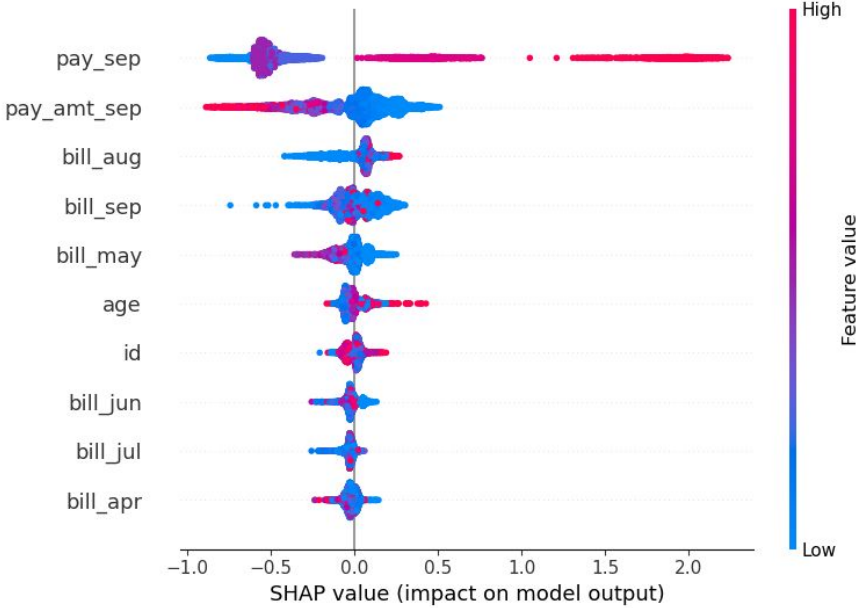
– Use smarter search (Optuna) to escape local optima

– Finer tuning to push class 1 performance up

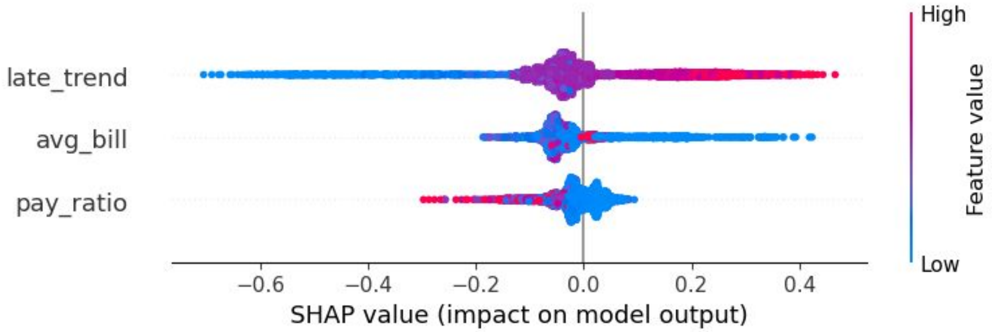
– Hoping for marginal lift from smaller false positive pool

What to try next?

- **Feature Importance (SHAP)**
  - how XGBoost is deciding
  - prioritize those features
- **Findings:**
  - pay_sep dominates → late payments spike default risk
  - Big bills (bill_aug, bill_sep, bill_may) push risk ↑
  - Higher payments (pay_amt_sep) pull risk ↓
  - Age tilts slightly (younger = riskier)
- **Hope: less noise & more focus => better model**

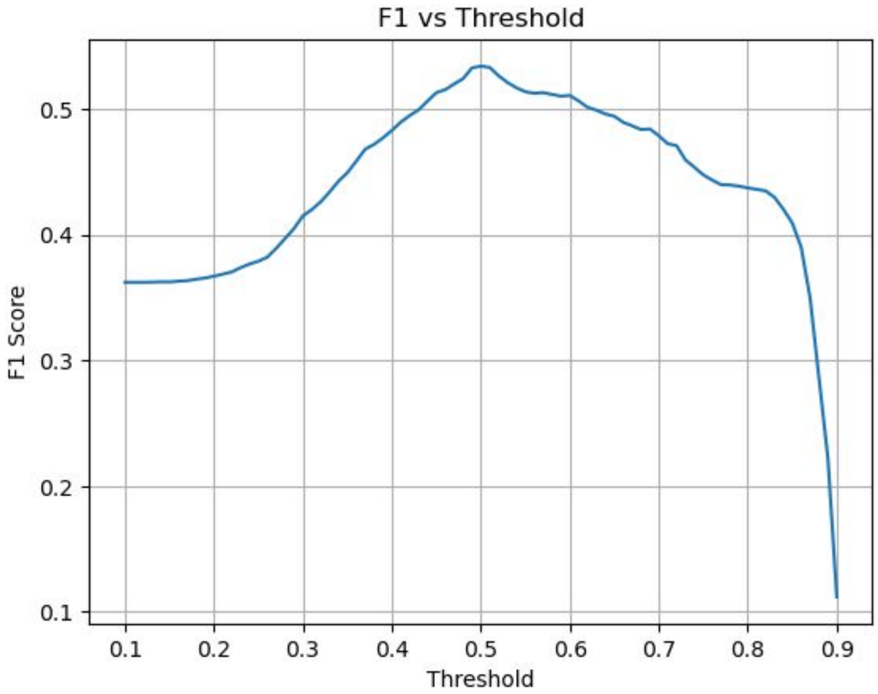


- **Feature Engineering**
  - Tuning & threshold both plateaued → model could use new signals



- **Goal: create relevant columns**
  - combining pay + bill history so trees can spot patterns
  - pay_ratio:
    (pay_amt_sep / bill_sep)
  - avg_bill:
    mean(bills Apr-Sep)
  - late_trend:
    (Sep bill – Aug bill)
  - missed_payments:
    # of billing cycles paid late
  - pay_amt_std
    stdev of payment amounts (how inconsistent they are)

- **Threshold Tuning**
  - find potentially more accurate F1 cut-off
  - default 0.50 cut-off might not fit skewed data
- **Findings**
  - F1 peaks ≈ 0.53 at threshold
  - turns out 0.50 was okay
  - Still worth trying
- Still worth trying



04 XGBoost v5

+ threshold tuning & new features

	precision	recall	f1-score	support
0	0.84	0.95	0.89	4673
1	0.67	0.35	0.46	1327
accuracy			0.82	6000
macro avg	0.76	0.65	0.68	6000
weighted avg	0.80	0.82	0.80	6000

Performance?

– precision on defaulters: 0.67 recall: 0.35 F1: 0.46
– recall ↑ from 0.34 → 0.35, F1 ↑ from 0.44 → 0.46
– accuracy: 82%
– modest lift shows new signals add value
– still not quite where I want it though

Thought Process:

– new frequency + volatility signals might catch more risk patterns:

– pay_ratio – September payment ÷ September bill size → “how much of the bill did they actually cover?”

- avg_bill – mean bill size from April-September → typical burden level

- late_trend – Sep payment minus Aug payment → catches worsening payment behaviour

- missed_payments – count of months with any late payment → frequency of being behind

- pay_amt_std – stdev of payments Apr-Sep → variability / inconsistency in what they pay

04 XGBoost v6

+ balancing classes

	precision	recall	f1-score	support
0	0.88	0.85	0.86	4673
1	0.52	0.58	0.55	1327
accuracy			0.79	6000
macro avg	0.70	0.71	0.70	6000
weighted avg	0.80	0.79	0.79	6000

Thought Process:

– dataset's been imbalanced (most people pay their debts! => class 0 > class 1
- likely why recall's been low
- balanced it w/ XGB's built-in class weighting
(scale_pos_weight = #neg/#pos)
– gave extra weight to defaulters so model focuses on true positives
– found F1-maximizing cutoff again (~0.55)

Performance?

– recall jumped from 0.38 → 0.58, F1 from 0.48 → 0.55
– precision dipped from 0.65 → 0.52
– accuracy ~80% held steady
– class weighting + threshold tuning outperformed oversampling for feature set

04 XGBoost v7

+ isotonic calibration

	precision	recall	f1-score	support
0	0.88	0.84	0.86	4673
1	0.51	0.59	0.55	1327
accuracy			0.79	6000
macro avg	0.70	0.71	0.70	6000
weighted avg	0.80	0.79	0.79	6000

Thought Process:

– raw XGB scores weren't true probabilities (e.g., 0.60 didn't equal 60 % default risk)
– used CalibratedClassifierCV (method = 'isotonic', cv = 5); adds small "stretch/ squeeze" curve to match model's raw scores w/ reality
=> best isotonic threshold: 0.26

Performance?

– precision 0.51, recall 0.59, F1 0.55 (same F1 as before)
– now probabilities are trustworthy: a 0.40 score ≈ 40 % observed default rate
– calibration gives better decision flexibility without hurting headline metrics

Final Model (at least for now)

Class 1 (defaulters):
- precision 0.51 → half the flagged borrowers do default
recall 0.59 → we catch ~6 out of 10 real defaulters
F1 0.55 → our best balance so far

Class 0 (non-defaulters):
-precision 0.88
→ mostly true positives
-recall 0.84
→ only 16 % false positives

Overall Metrics
- accuracy 0.79 (skewed data, so less meaningful)
- macro-avg F1 0.70
→ solid, given 22 % positives

	precision	recall	f1-score	support
0	0.88	0.84	0.86	4673
1	0.51	0.59	0.55	1327
accuracy			0.79	6000
macro avg	0.70	0.71	0.70	6000
weighted avg	0.80	0.79	0.79	6000

Thanks!

Questions?

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