AI Models for Early Warning Systems (EWS) in Banking Credit Risks

A Machine Learning-Based Early Warning Framework for Consumer Credit Risk

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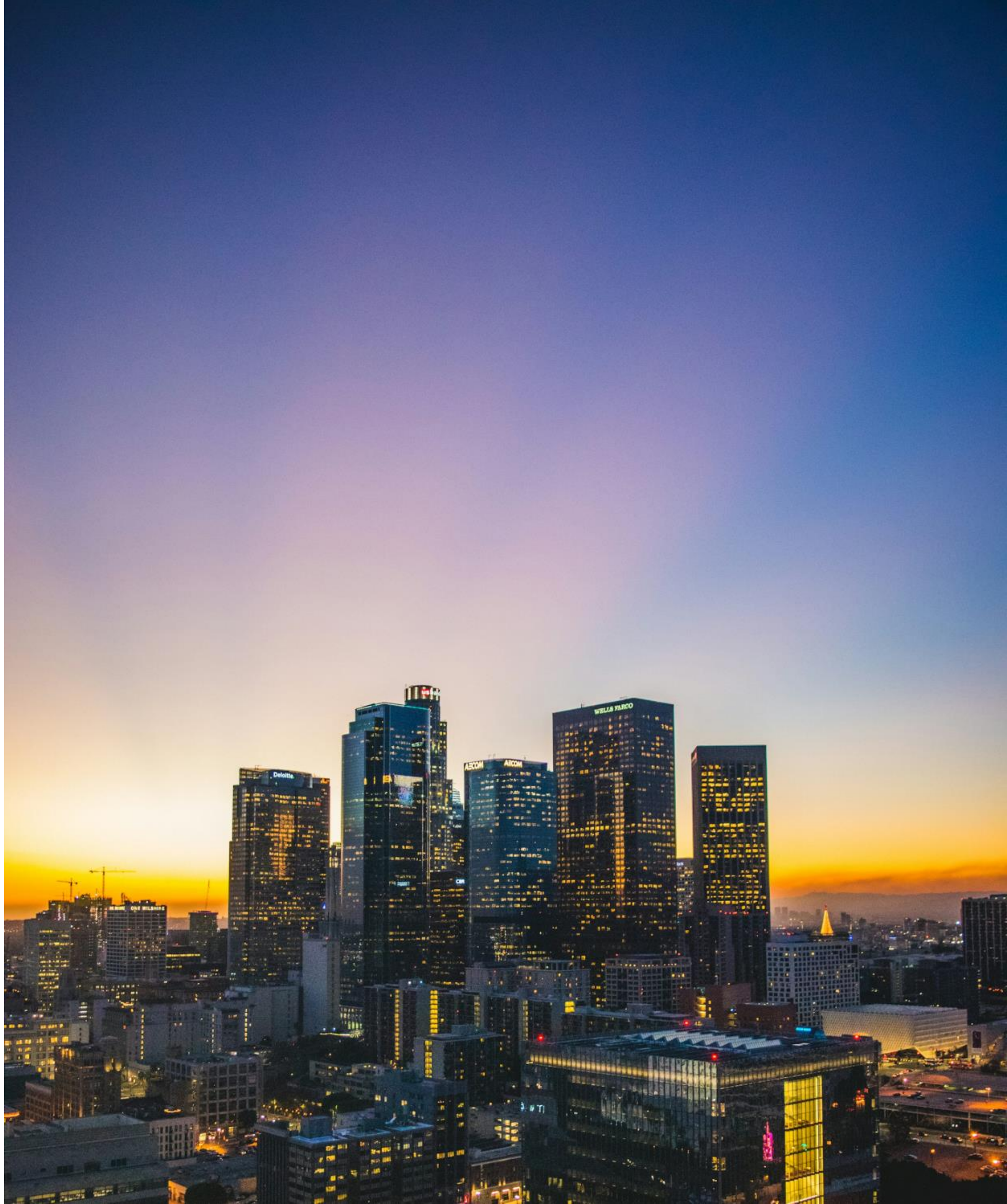
Credit Risk in Today's Economic Environment

- Household credit in Europe exceeds **€ 7 trillion,** strongly tied to consuptiom.

- Banks must balance **growth, risk apetite and capital constraints.**

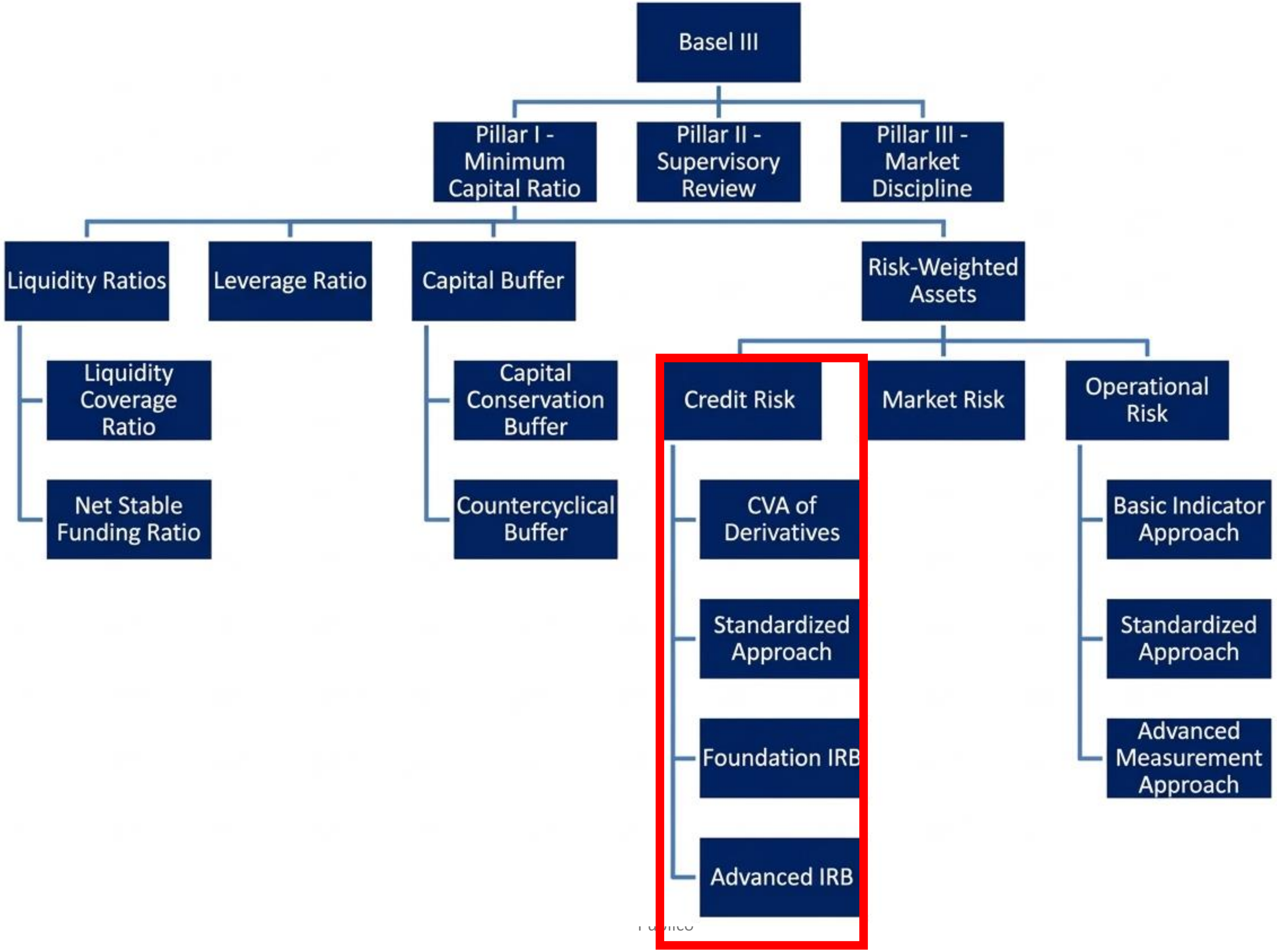
- Movements in interest rates worldwide and macroeconomic volatility increase credit uncertainty.

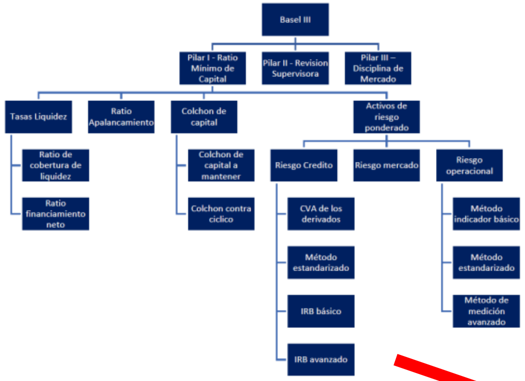
- Consumer protection and responsable lending are becoming central regulatory priorities.



and... based on what a bank could quantify credit risk to determine capital requirements..?

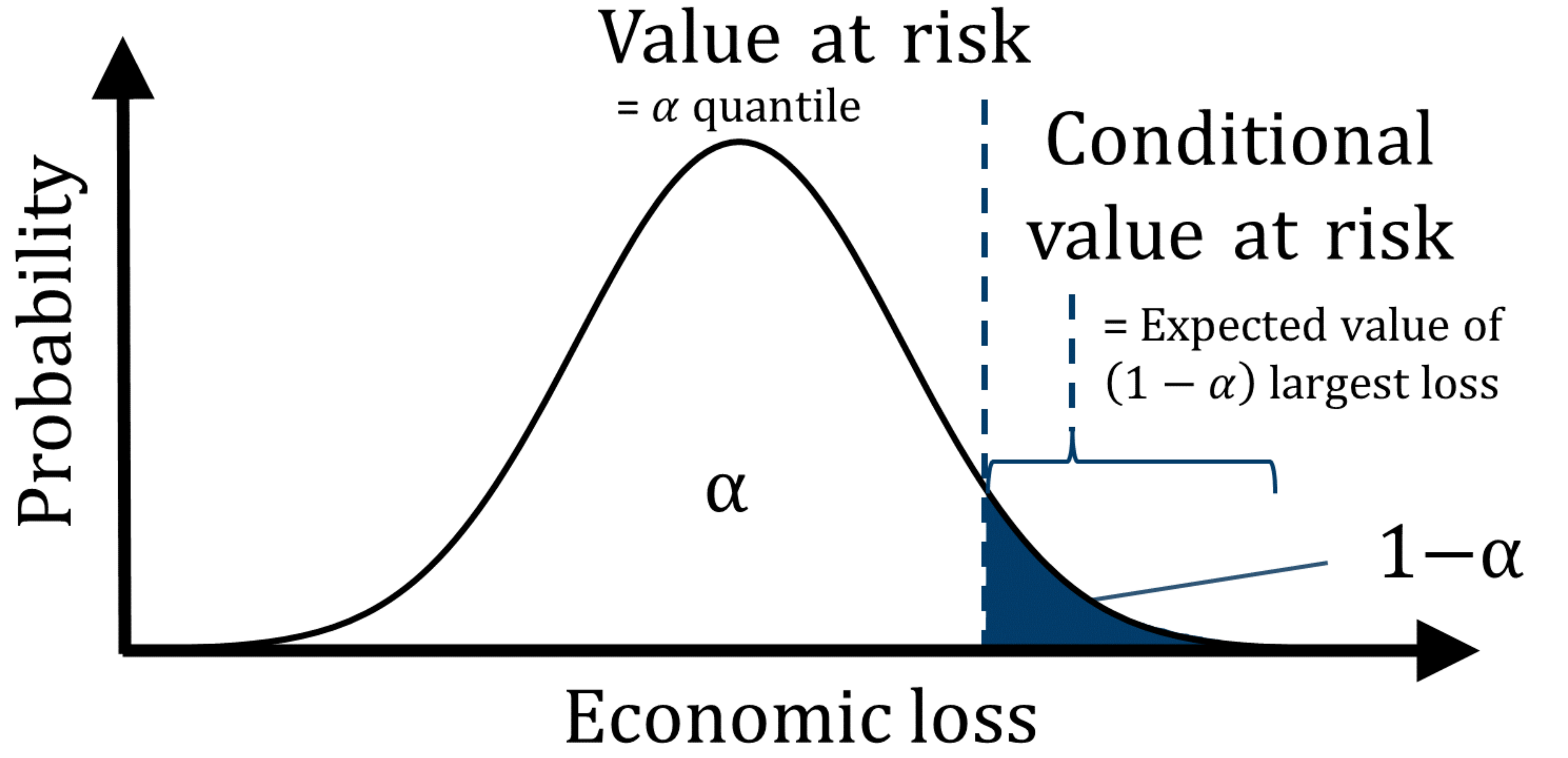
Regulatory Framework and Credit Risk Measurement


Basel III
Pillar I - Minimum Capital Ratio
Pillar II - Supervisory Review
Pillar III - Market Discipline
Liquidity Ratios
Leverage Ratio
Capital Buffer
Risk-Weighted Assets
Liquidity Coverage Ratio
Net Stable Funding Ratio
Capital Conservation Buffer
Countercyclical Buffer
Credit Risk
Market Risk
Operational Risk
CVA of Derivatives
Standardized Approach
Foundation IRB
Advanced IRB
Basic Indicator Approach
Standardized Approach
Advanced Measurement Approach



- **Standardized Approach**
- **IRB Method**
  - The bank builds its own, more precise and customized risk model.
  - It estimates which clients might default, how much it would lose, and which part of the exposure carries the risk.

$$EXPECTED\ LOSS = \boxed{PD * LGD * EAD}$$



Core Components of Credit Risk Models

$$EXPECTED\ LOSS = \boxed{\boldsymbol{PD}} * \boldsymbol{LGD} * \boldsymbol{EAD}$$

PD (Probability of Default)

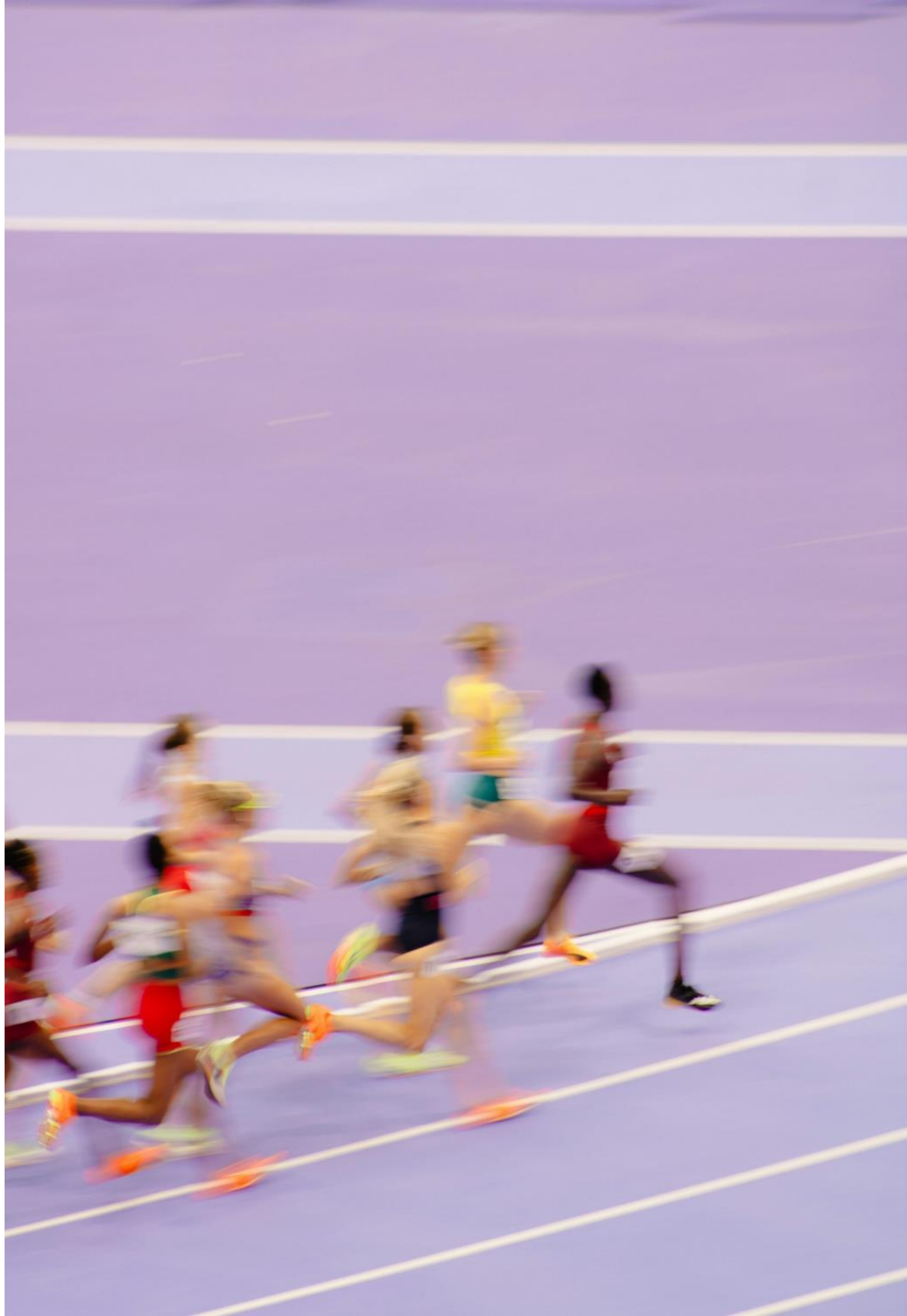
LGD (Loss Given Default)

EAD (Exposure at Default)

The AI Revolution in Finance

AI is rapidly transforming financial institutions

- Explosion of **data availability**
- Increased **computing power**
- Advances in **machine learning algorithms**



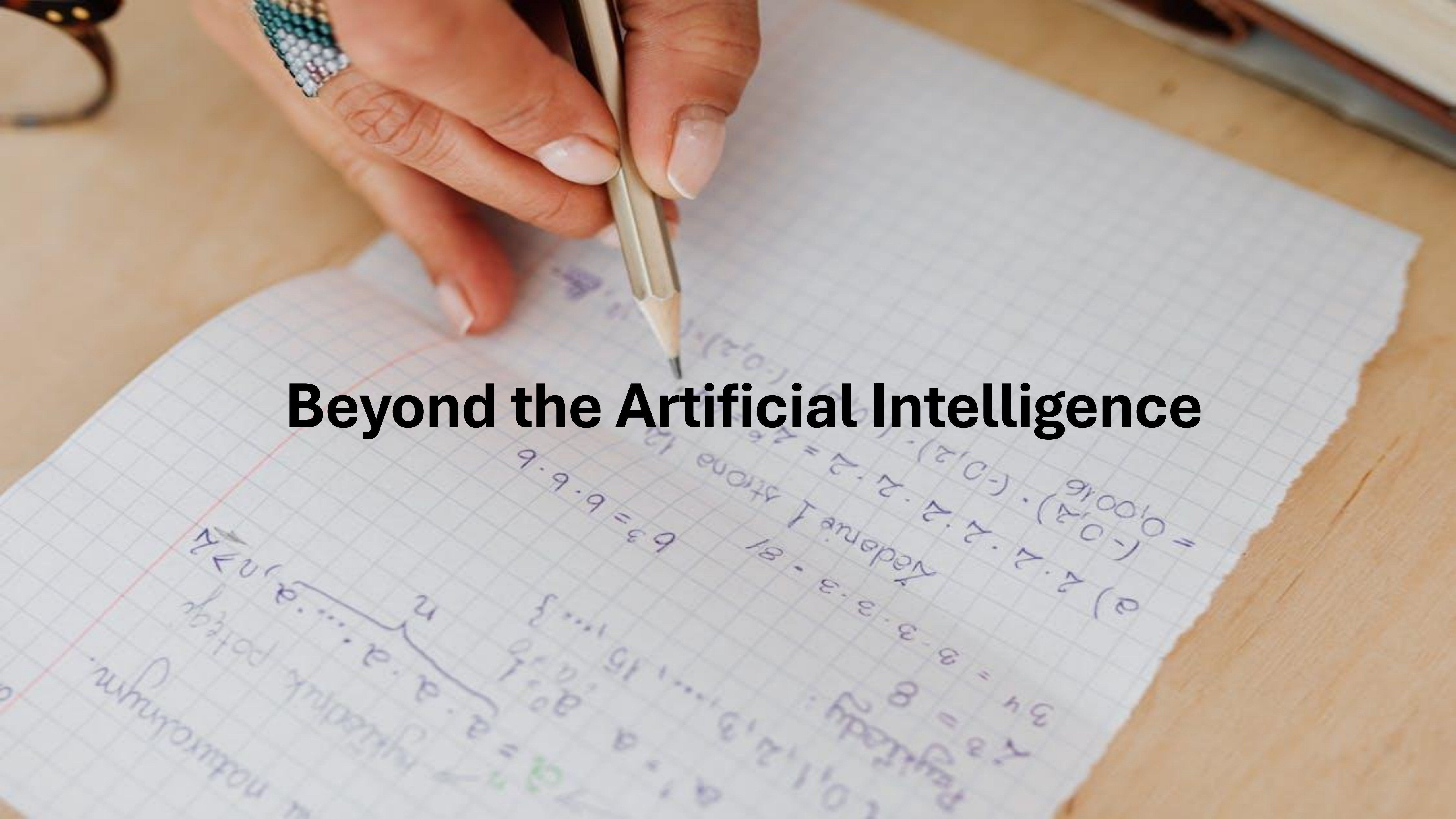
Applications in Banking include

- Credit Scoring
- Fraud Detecting
- Risk Modelling
- Customer behavior prediction

But the key question is:

Can AI improve how we anticipate credit deterioration?

Beyond the Artificial Intelligence

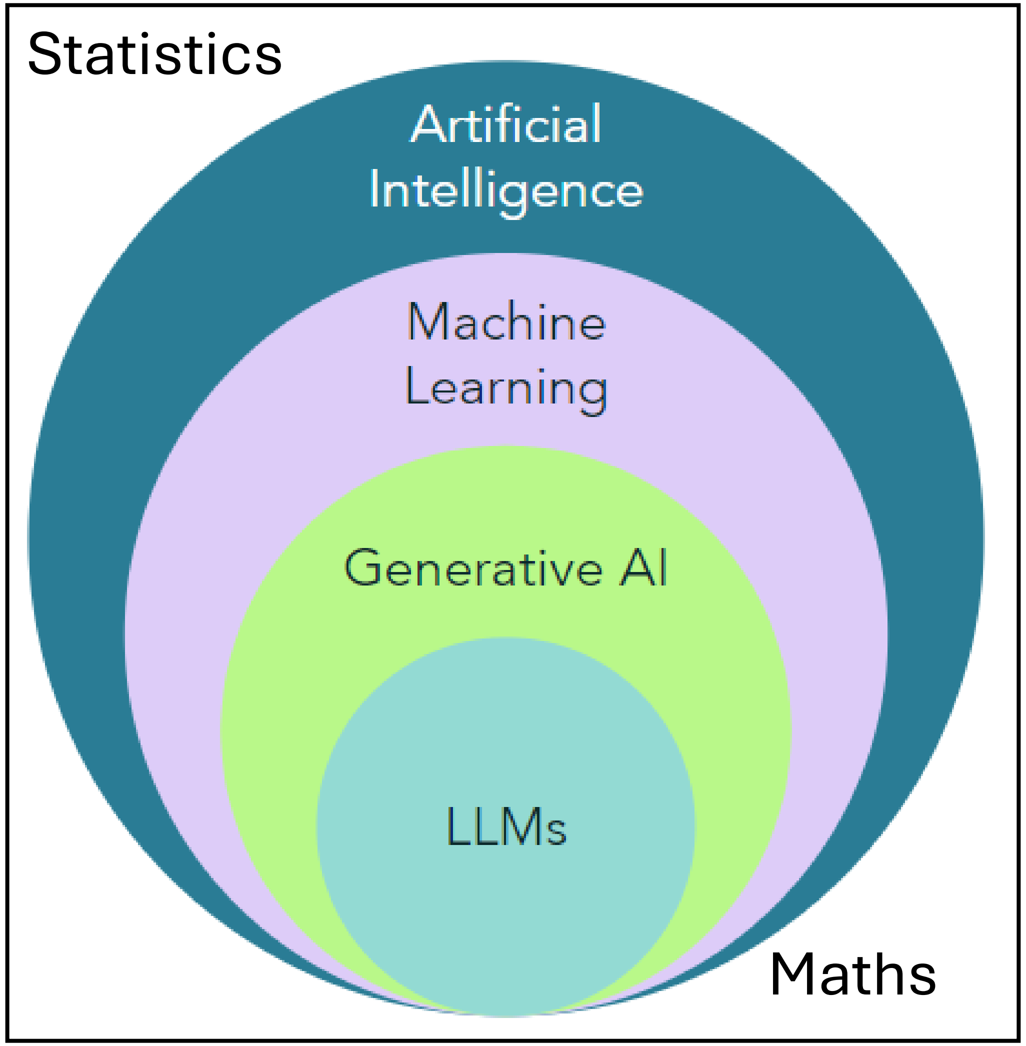


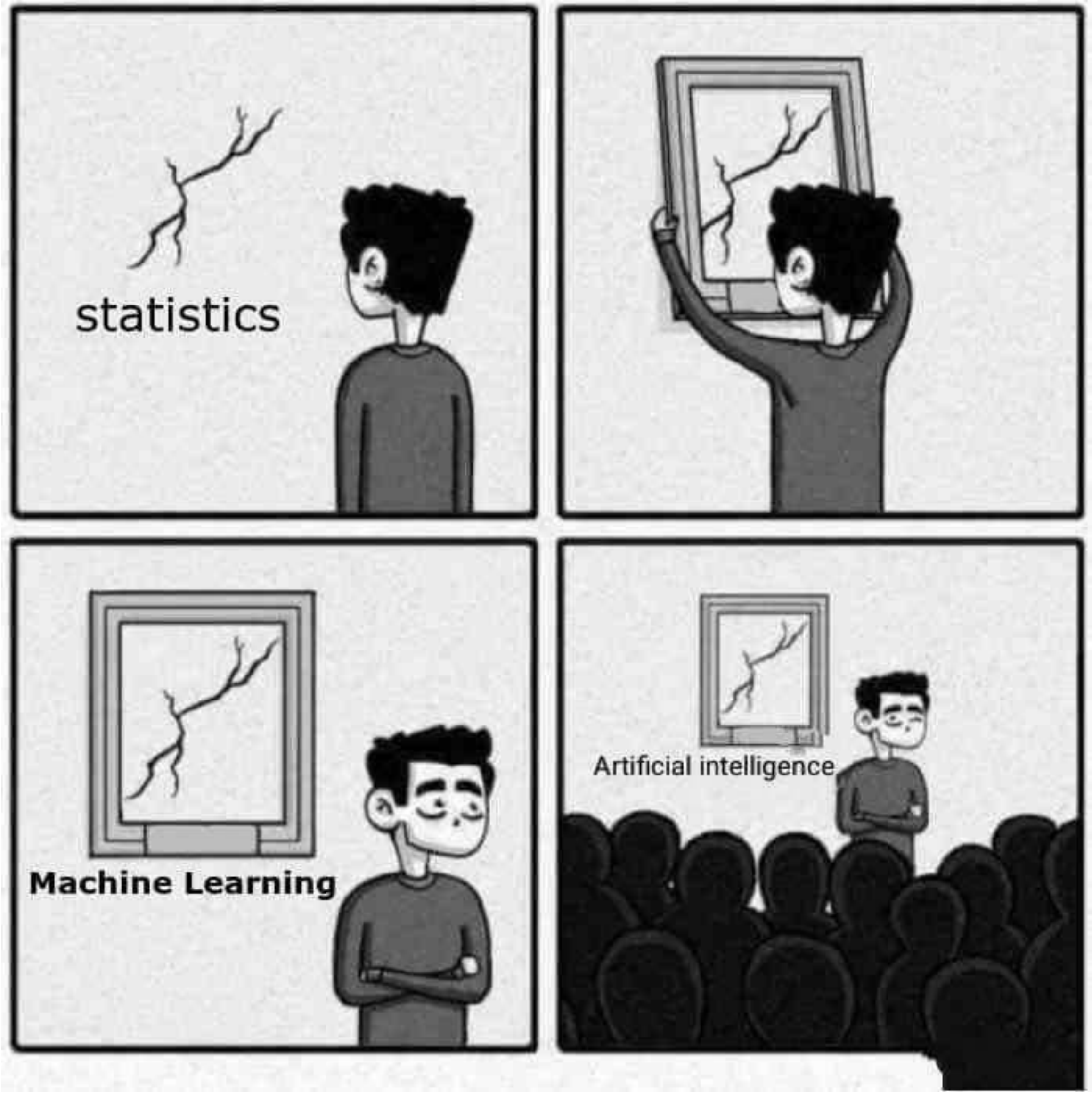
Artificial Intelligence is built on Statistics

Every AI model is fundamentally based on statistical principles

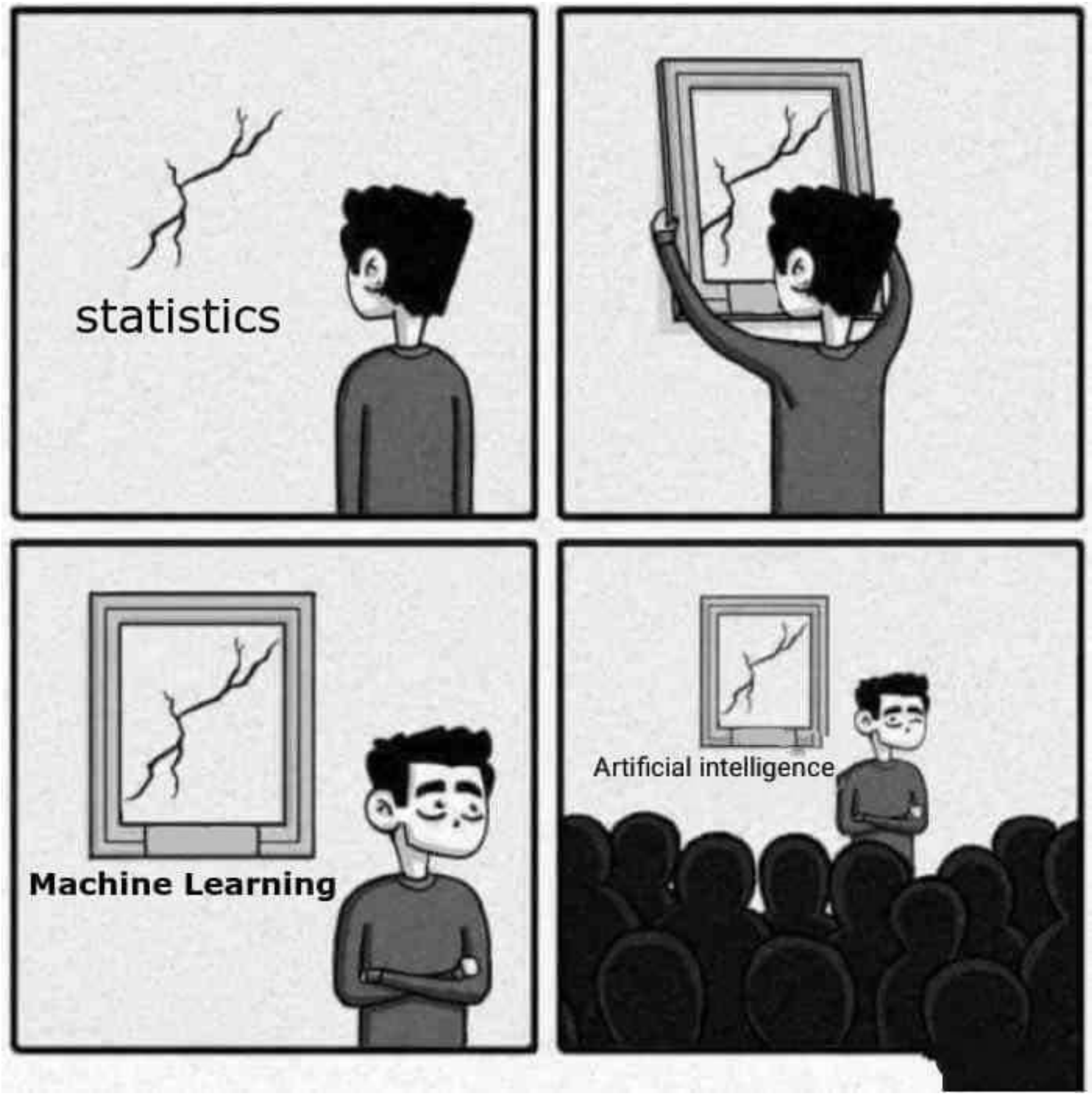
- Models learn patterns from historical data
- Algorithms optimize statistical relationships
- Predictions rely on statistical inference

Artificial Inteligence framework





ML may be the frame..
AI the gallery....
but
Statistics is the picture that holds it all together.



Statistics is the picture that holds it all together.

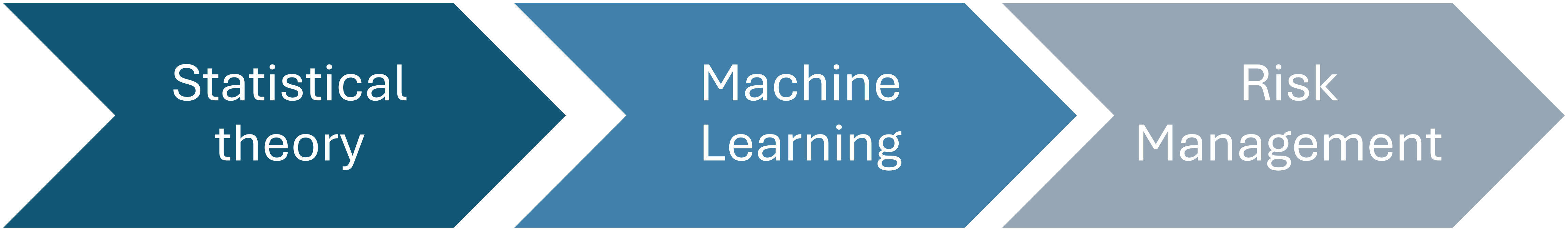
However for actuaries, this foundation is not new, it is our comparative advantage

How Actuarial Science intersects with AI and Credit Risk

Actuarial Science has long focused on risk quantification and prediction

- Statistical modelling of uncertainty
- Probability-based risk assessment
- Experience with regulatoy frameworks
- Long-term risk forecasting

Actuaries are uniquely positioned to bridge



Current Context of the Banking Industry

Banks operate today in an environment characterized by:

- Increasing credit portfolio complexity
- Growing regulatory pressure
- Large volumes of costumer and transactional data
- Need for faster and more accurate risk monitoring

Traditional credit risk models often rely on:

- Periodic financial information
- Static borrower characteristics

What would be the challenge..?

- Transforming large amounts of data into actionable risk insights

- Banks today have more data tan ever before, but extracting menaningful risk signals remains a challenge

What is a Early Warning Systems (EWS)

Typical Objetives EWS

- Identify borrowers with **increasing probability of default**
- Detect **behavorial changes in financial activity**
- Support **proactive risk management**

EWS Benefits for financial institutions

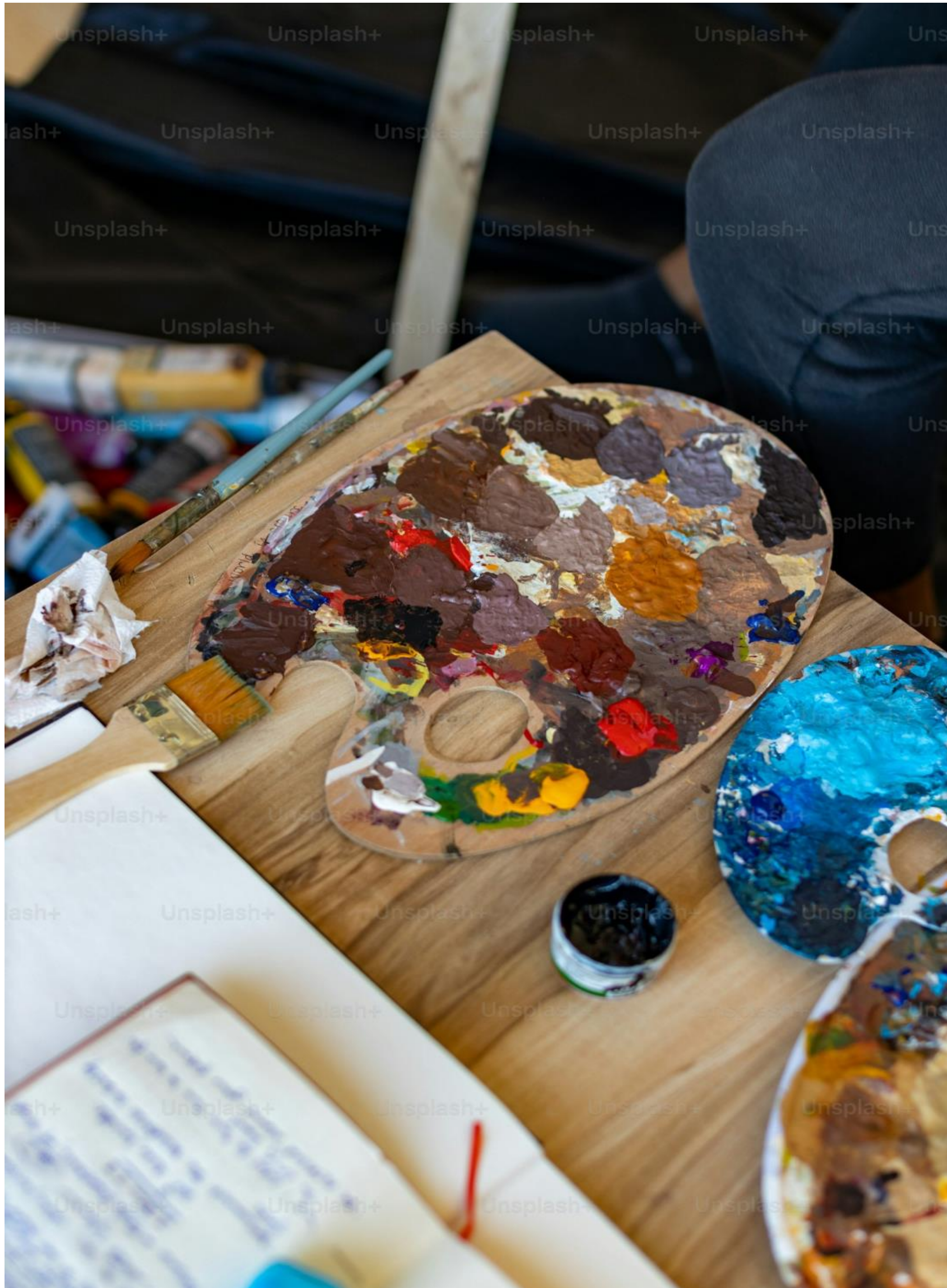
- Earlier **risk mitigation actions**
- Improved **portfolio monitoring**
- Reduced **credit losses**

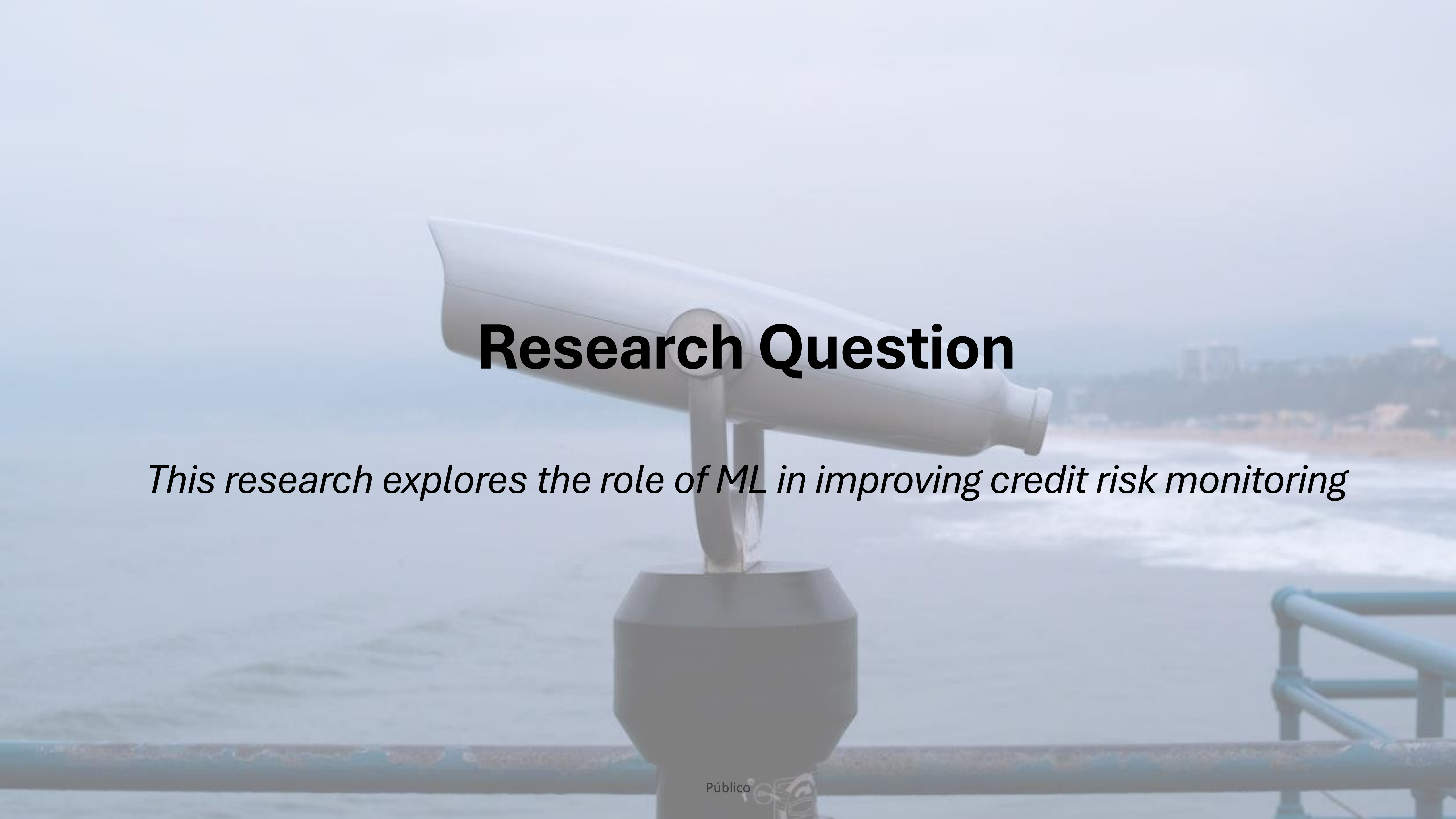
Modern EWS increasingly combine

- Traditional **credit risk models**

- **Machine learning techniques**

- **Behavorial and transactional data**





Research Question

This research explores the role of ML in improving credit risk monitoring

Can ML models improve the detection of early signals of credit deterioration in consumer lending?

- Which ML models perform best for this task?
- Can these models provide interpretable risk signals?
- How effective are they in supporting EWS?

Main Objetive

To evaluate wheter ML can enhance early risk detection compared with traditional approaches

Model Development

Workpath

Data Explore and preprocessing

ML classification training for PD

Risk Assessment

ML regression training for EWS

Early Warning System

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Early Warning System

Data Description

The analisis is based on consumer credit portfolio data from a financial institution

Data Overview

Main characteristics:

- 307.511 clients
- 112 explanatory variables
- Information on borrower financial and behavioral characteristics

Data Explore

Index	TARGET	AMT_INCOME_TOTAL	AMT_CREDIT	...	AMT_GOODS_PRICE	CNT_FAM_MEMBERS
count	307511	307511	307511	...	307511	307511
mean	0,08	168.797	599.025	...	538.396	2
std	0,27	237.123	402.490	...	369.446	0,91
min	0	25650	45000	...	40500	1
25%	0	112500	270000	...	238500	2
50%	0	147150	513531	...	450000	2
75%	0	202500	808650	...	679500	3
max	1	117000000	4050000	...	4050000	20

Objetive of the dataset

- To analyze patterns associated with credit deterioration and default risk, enabling the development of an EWS.

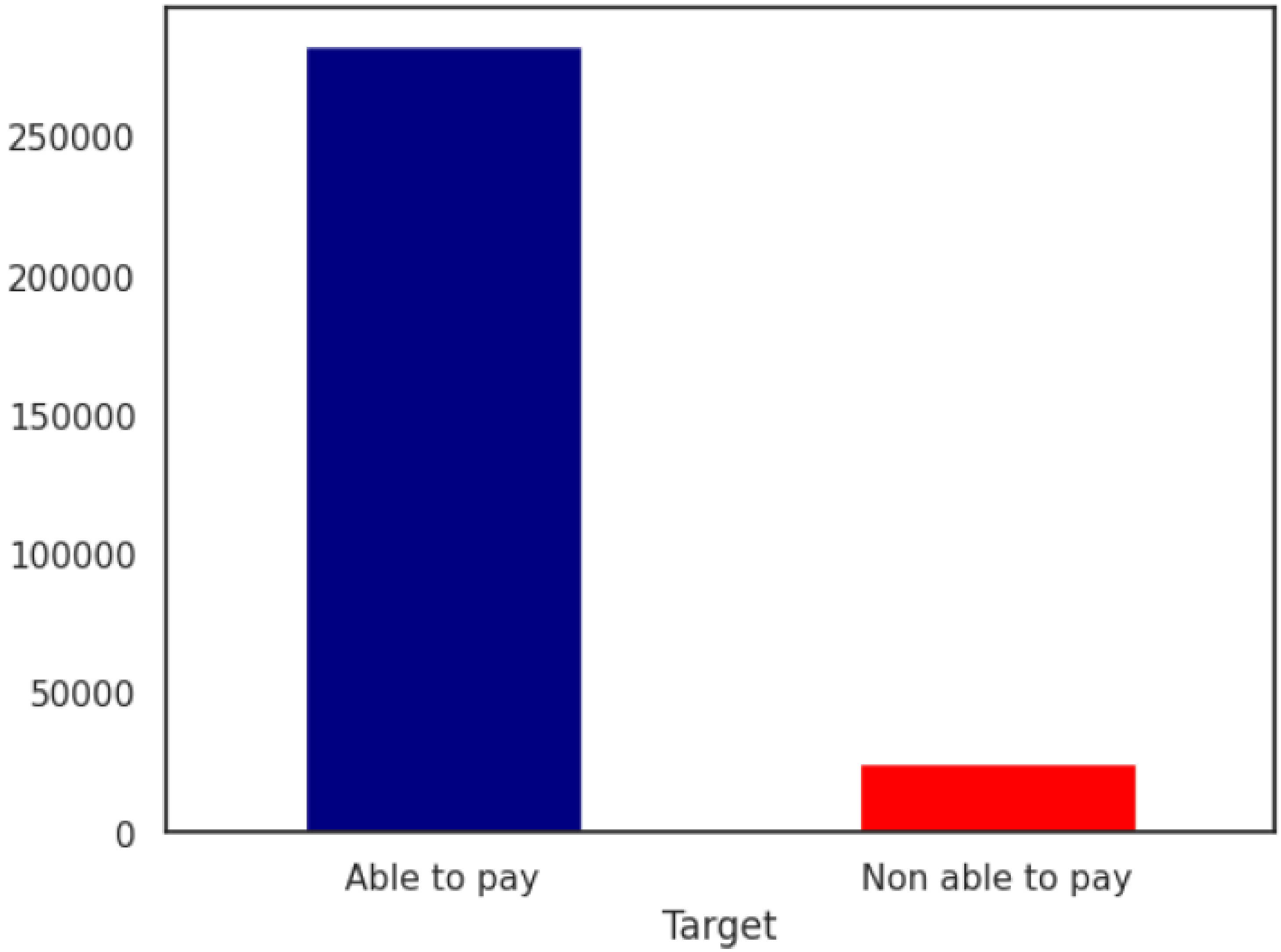
Type of Variables

- **Socio-economic** (Incomes, Educaction level, employment...)
- **Financial** (Loan amount, credit exposure, colateral availability..)
- **Behavioral** (Payment history, account activity, credit patterns..)
- **Geographical** (Region, Neighbourhood...)

These variables provide multiple dimensiones of borrower risk, allowing the detection of patterns associated with potential default.

Target Variable

The modeling objetive is the prediction of **default risk.**



Data Preprocessing

before applying any model, the dataset must be prepared to ensure data quality and model reliability

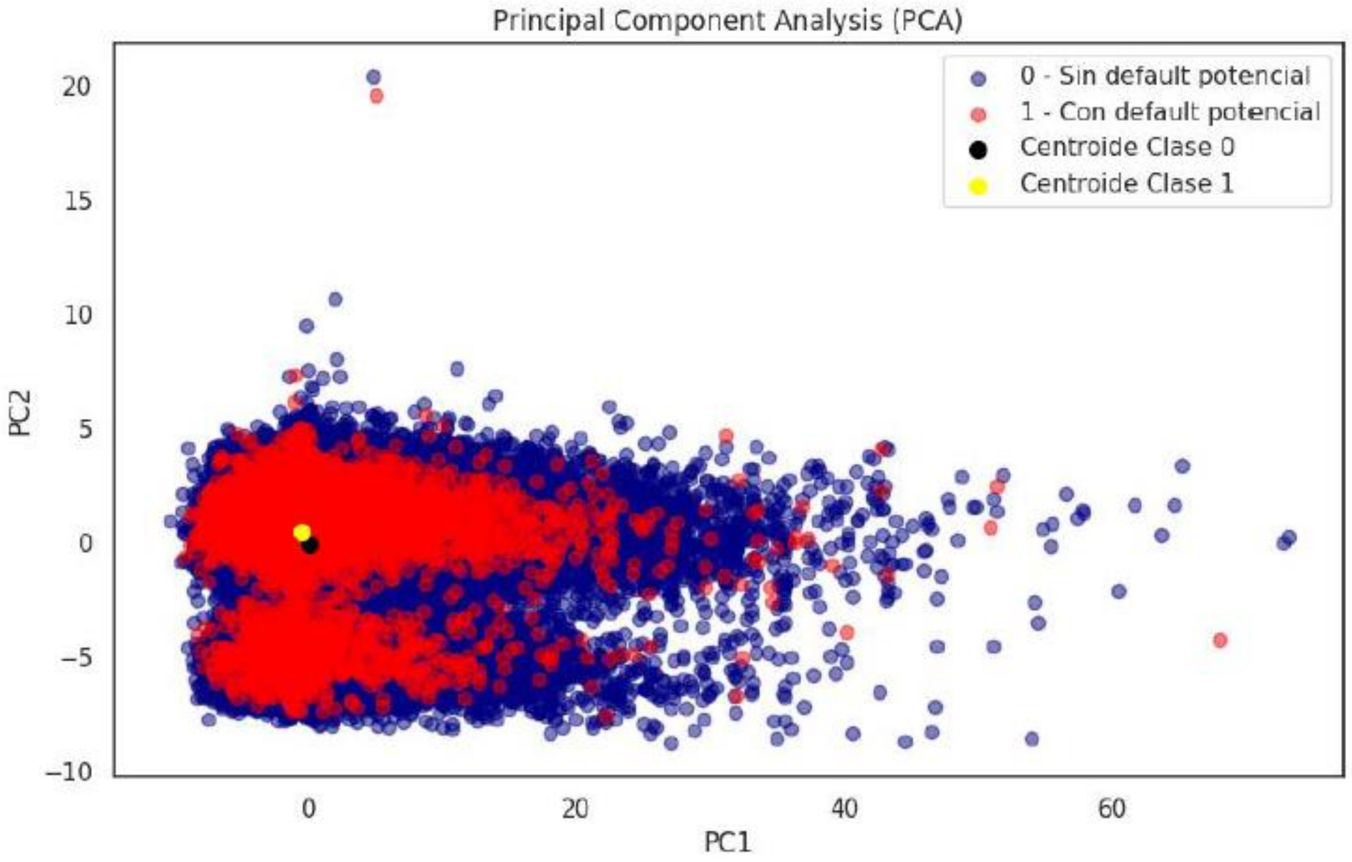
Data preprocessing

- Data cleaning
- Analysis of Target Variable
- Feature transformation
- Normalization and scaling

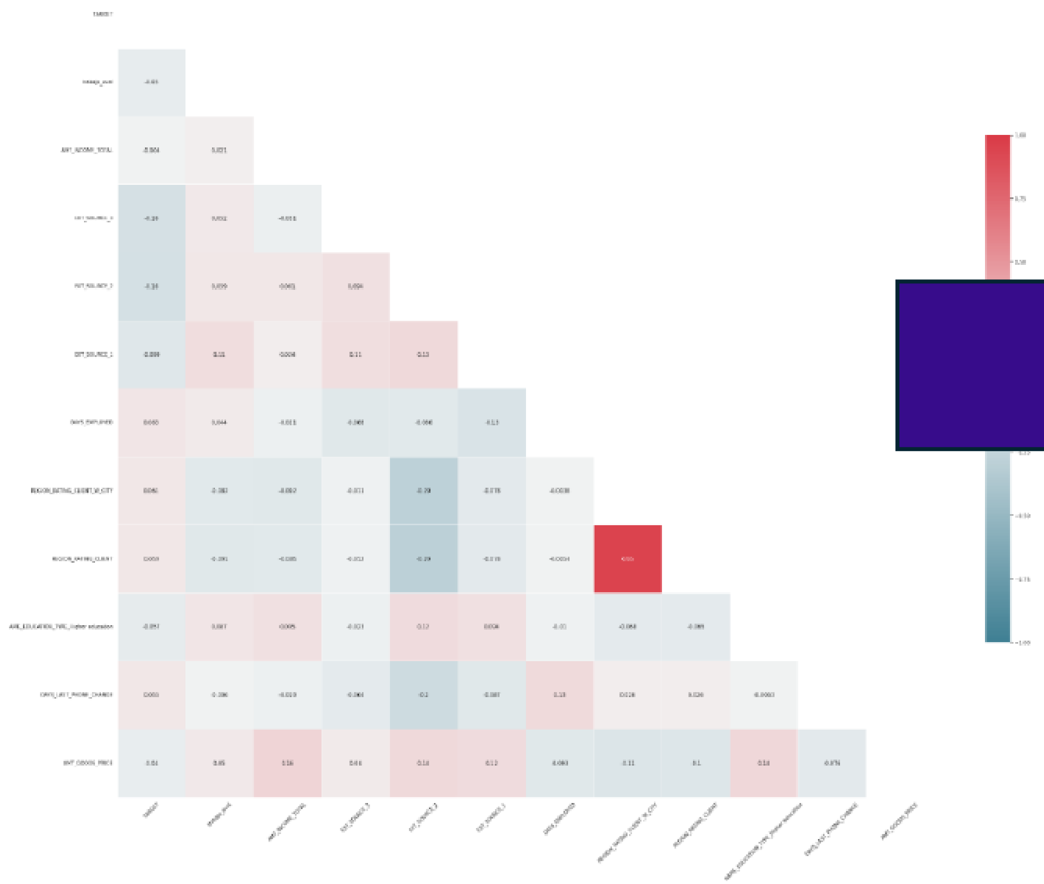
We are looking how to improve model stability, interpratibility and predictive performance

Principal Component Analysis (PCA)

PCA helps identify dominant patterns and reduce dimensionality.



Correlation analysis



307.511 clients
11 high-correlated variables with target one

Data transformation

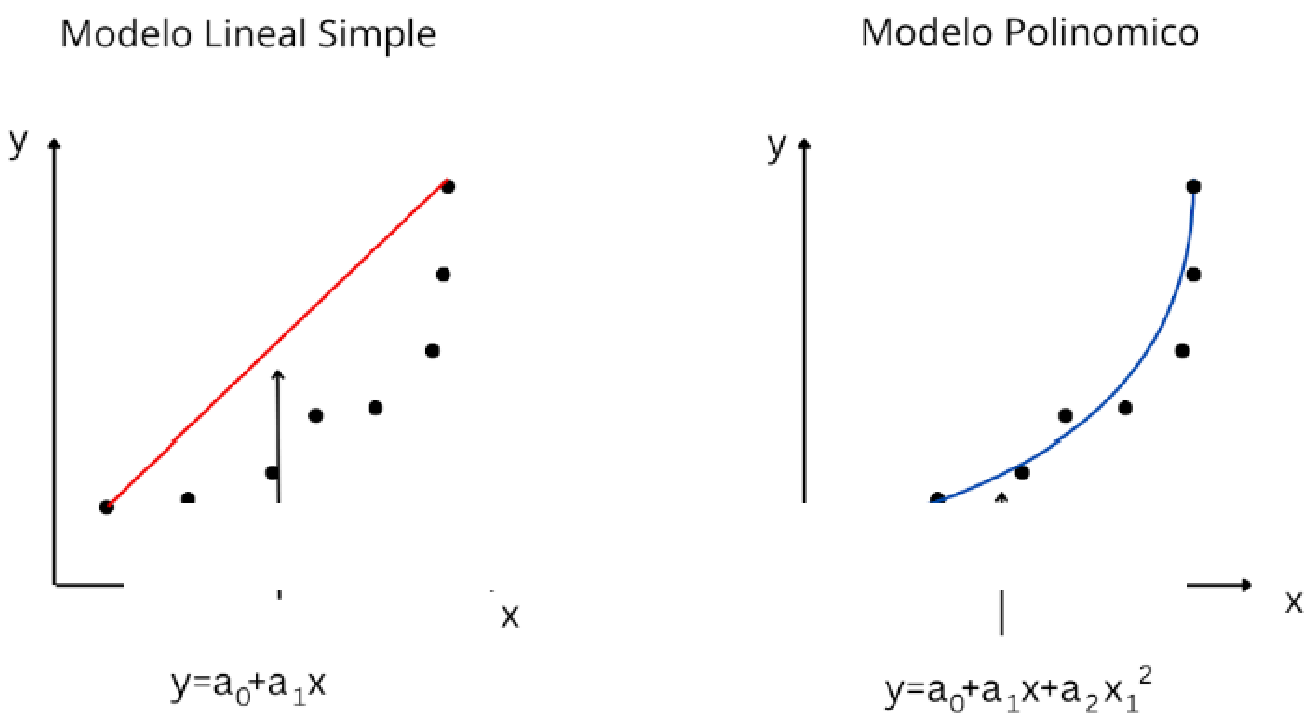
One-hot encoding

- widely used technique in data preprocessing to convert categorical variables into a numerical format suitable for machine learning models.

Gender	Location
Male	South
Female	North
Male	West
Male	East

Gender_Male	Gender_Female	Location_South	Location_North	Location_West	Location_East
1	0	1	0	0	0
0	1	0	1	0	0
1	0	0	0	1	0
1	0	0	0	0	1

Polynomial Features

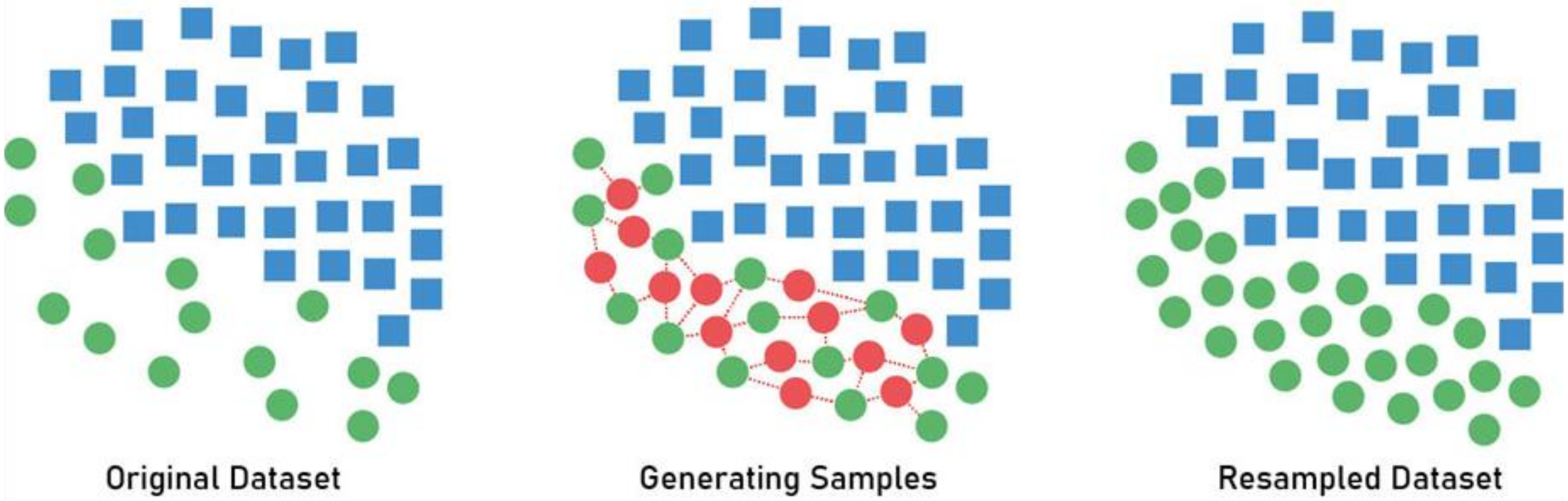


- Capturing nonlinear relationships between variables
- The degree will depend on the nature of the problem

$$Salary^2 * HigherEducation$$

SMOTE (Synthetic Minority Over-Sampling Technique)

A preprocessing method used to address class imbalance. Instead of duplicating minority samples, SMOTE creates synthetic ones.



- For example, if two similar delinquent customers owe 1000 and 1100, the algorithm generates a new sample at 1050.
- This helps the model learn minority-class patterns more effectively without losing information.

Final Modelling Dataset

Clients	Variables
307.511	91

ML Models Evaluated

Model Evaluation Strategy: Beyond the Models

Why so many ML models?

Because every real-world problem has different shapes:

noisy data, non-linear patterns, few samples, too many features, class imbalance…

A single model can’t master all terrains.

MODELING METHODOLOGY: ML MODELS FOR RESEARCH

1 Baseline Statistical Models

Logistic Regression
Probabilistic model for binary classification

2 Classical ML Models

Naive Bayes
$P(A|B)$
Algorithm based on Bayes' theorem

Decision Tree
Graphical model for decisions and classification

Random Forest
Ensemble of decision trees (Bagging)

3 Advanced ML Models

3.1 Artificial Neural Networks (ANN)

Model inspired by brain biology (Deep Learning)

3.2 Gradient Boosting Models

XGBoost
eXtreme Gradient Boosting - Optimized and efficient

LightGBM
Light Gradient Boosting Machine - Fast on large datasets

CatBoost
Categorical Boosting - Effective handling of categorical variables

Workpath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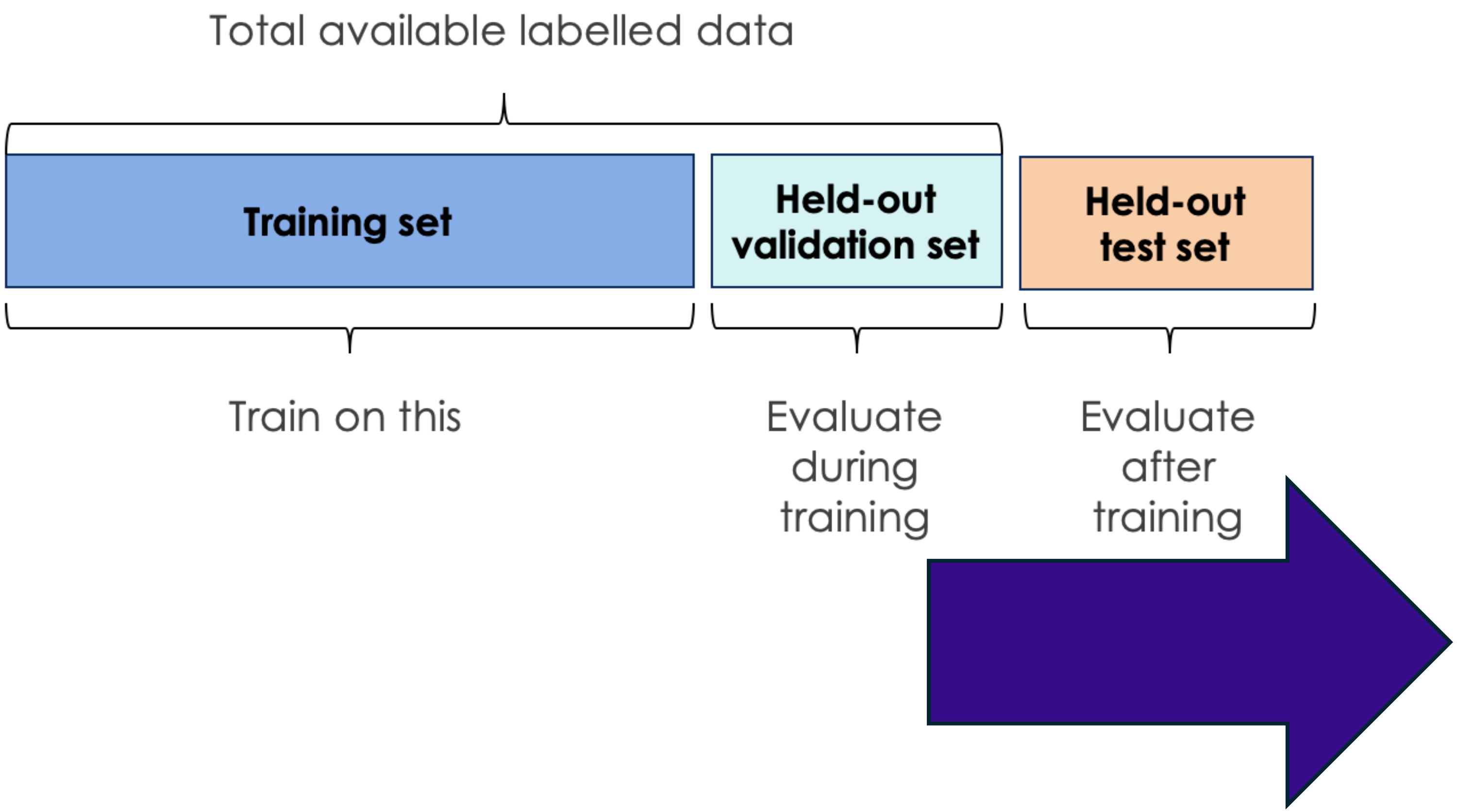
Early Warning System

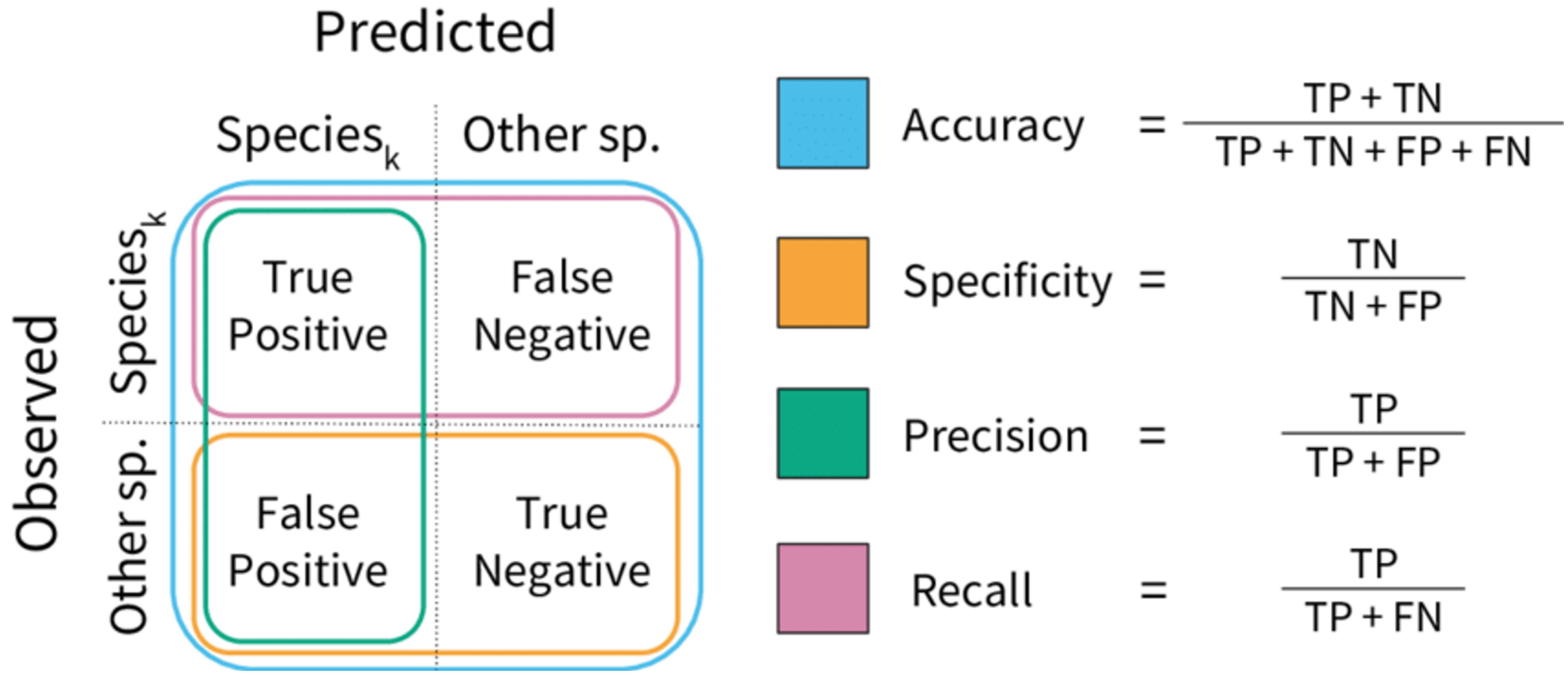
Traintestsplit()



Category	Size
Training set	246.008
Testing set	61.503

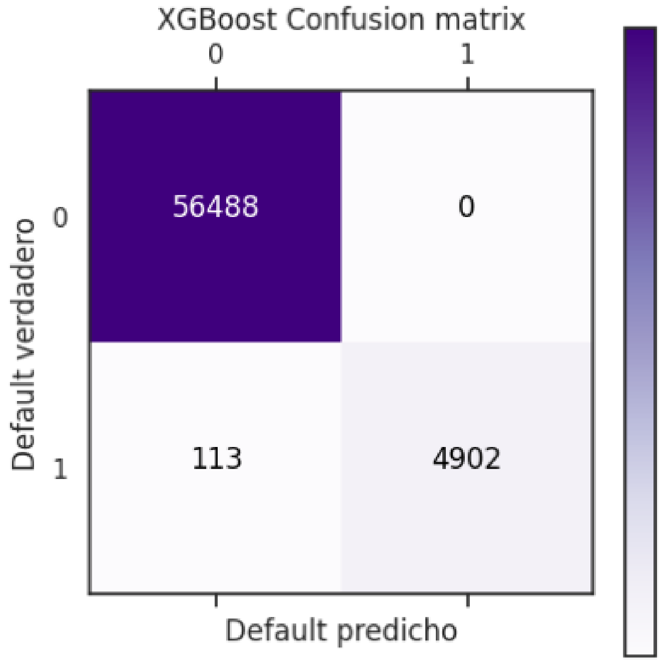
Model Evaluation

Regarding the classification* nature of the problem:

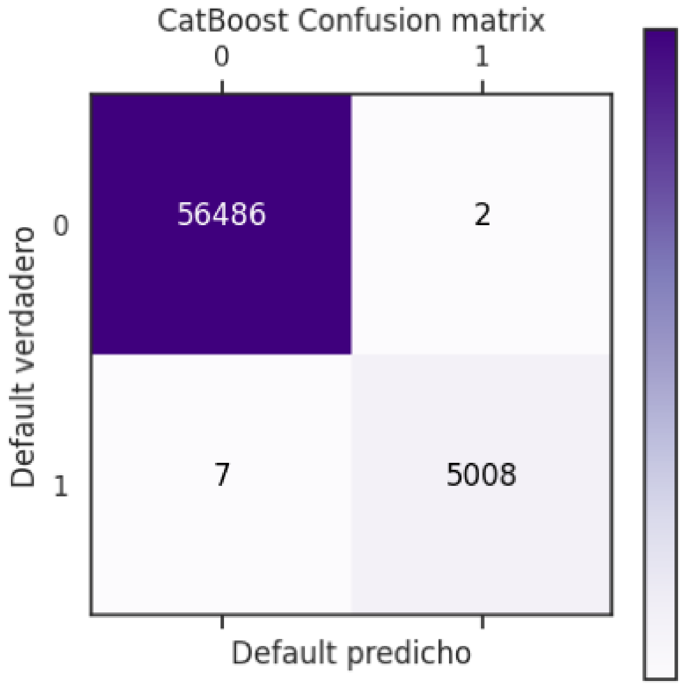


The model predicts discrete categories

Best Performing Models



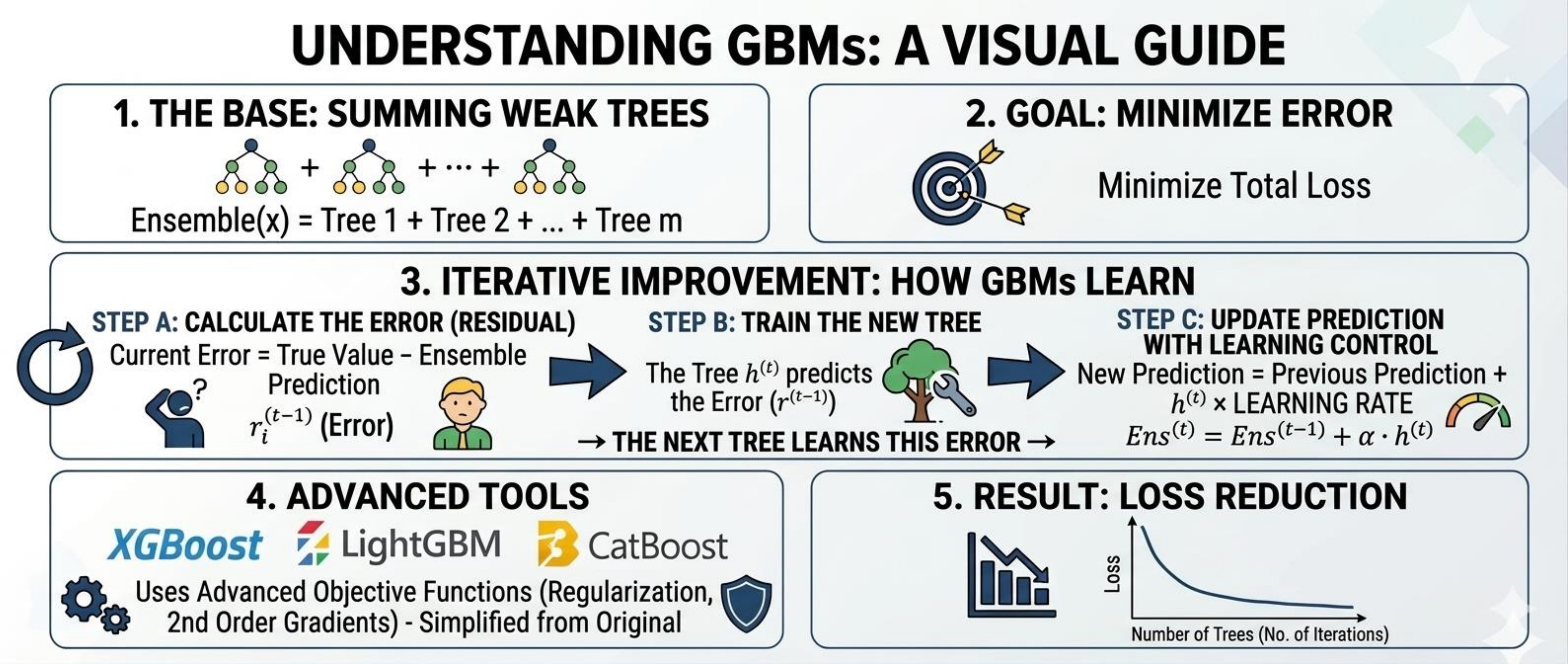
METRIC	RESULT
CROSS-VALIDATION	99,87%
ACCURACY	99,81%
F1-SCORE	98,86%



METRIC	RESULT
CROSS-VALIDATION	99,42%
ACCURACY	99,96%
F1-SCORE	99,91%

Why Gradient Boosting Models Stand Out

- Ability to model nonlinear relationships
- Effective handling of features interactions
- Robustness with large datasets
- Excellent performance with limited hyperparameter tuning
- Complex interactions


UNDERSTANDING GBMs: A VISUAL GUIDE
1. THE BASE: SUMMING WEAK TREES
+ ⋯ +
Ensemble(x) = Tree 1 + Tree 2 + ... + Tree m
2. GOAL: MINIMIZE ERROR
Minimize Total Loss
3. ITERATIVE IMPROVEMENT: HOW GBMs LEARN
STEP A: CALCULATE THE ERROR (RESIDUAL)
Current Error = True Value – Ensemble Prediction
$r_i^{(t-1)}$ (Error)
STEP B: TRAIN THE NEW TREE
The Tree $h^{(t)}$ predicts the Error ($r^{(t-1)}$)
→ THE NEXT TREE LEARNS THIS ERROR →
STEP C: UPDATE PREDICTION WITH LEARNING CONTROL
New Prediction = Previous Prediction + $h^{(t)}$ × LEARNING RATE
$Ens^{(t)} = Ens^{(t-1)} + \alpha \cdot h^{(t)}$
4. ADVANCED TOOLS
XGBoost
LightGBM
CatBoost
Uses Advanced Objective Functions (Regularization, 2nd Order Gradients) - Simplified from Original
5. RESULT: LOSS REDUCTION
Loss
Number of Trees (No. of Iterations)

How to get the key Insights from the Models

- **Mean Decrease in Gini**

Measure how much each variable contributes to reducing uncertanty in the model

- **SHAP values**

Quantify the contribution of each variable to individual predictions

Key Insights from the Models

These methods allow us to:

- Identify key drivers of default risk
- Understand model behavior
- Ensure results are interpretable and actionable

Key Insights from the Models

Borrower characteristics matter

- *Income, employment, stability and education level are importat predictors to default*

Behavioral indicators provide strong signals

- *Payment behavior and credit utilization are critical early indicators of credit deterioration*

ML improves pattern detection

- *Advanced algorithms capture complex relationships that traditional models may miss*

Early Warning System (EWS)

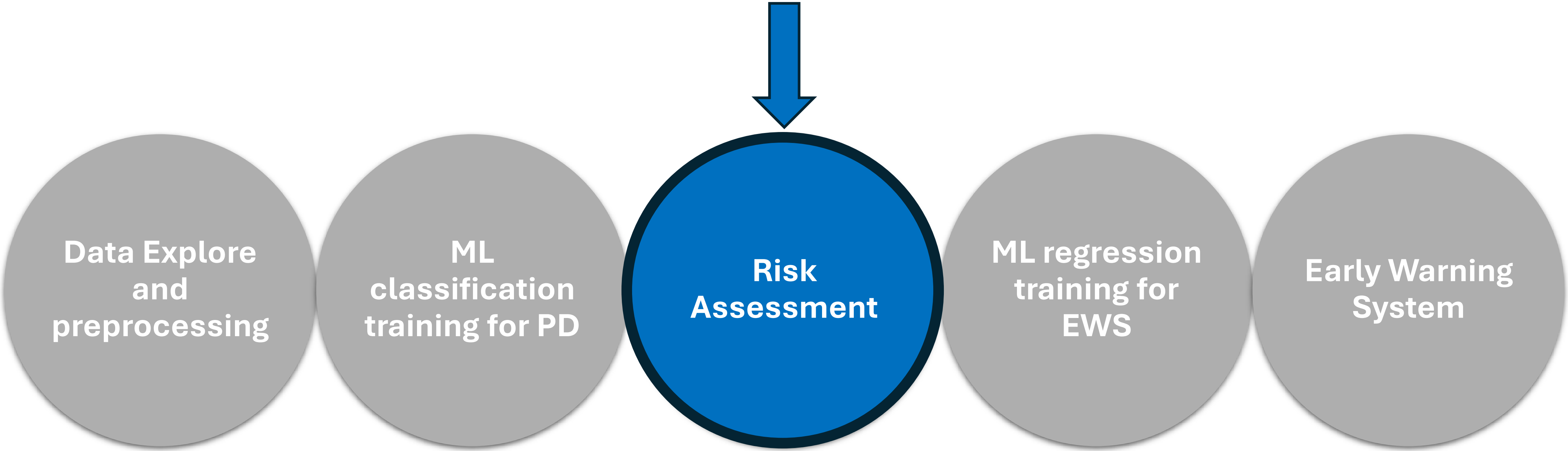
from prediction to decision-making tool

Objective (EWS)

- Identify high-risk borrowers at an early stage
- Enable proactive risk management actions

The system transforms model predictions into actionable risk signals.

Workpath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Risk Assesment

Relevant variables Identification

Risk Ranges

IRB

EWS Development

- Select variables with the highest relative influence
- Create risk-level ranges based on variable behavior
- Define ranges according to each variable's nature
- Generate and integrate the results into the IRB framework

Discretization of variables

Discretization of variables (e.g., transforming salary into decile-based features such as Salary_Decile10, Salary_Decile20...) to study variable importance and non-linear patterns.

Risk Category	DISCRETIZED VARIABLES
AMT_INCOME_TOTAL	AIT(1)...AIT(10)
AMT_GOODS_PRICE	AGP(1)....AGP(10)
DAYS_EMPLOYED	DEMP(1)...DEMP(10)
DAYS_LAST_PHONE_CHANGE	PCH(1)...PECH(10)
EXT_SOURCE_1	EX1(1)...EX3(10)
EXT_SOURCE_2	EX2(1)...EX2(10)
EXT_SOURCE_3	EX3(1)...EX3(10)

EWS - IRB Annex Basel III

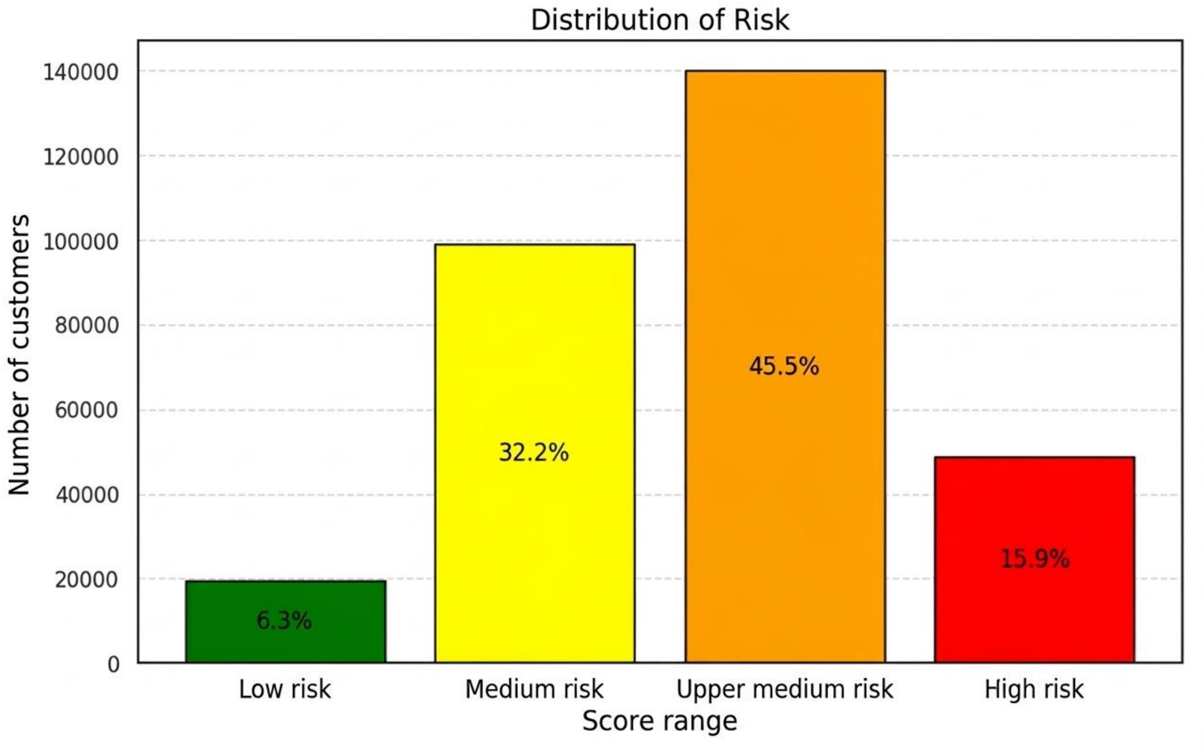
- The logic behind this binning approach is to assign an increasing or decreasing weight to each range, reflecting its contribution to the probability of default.

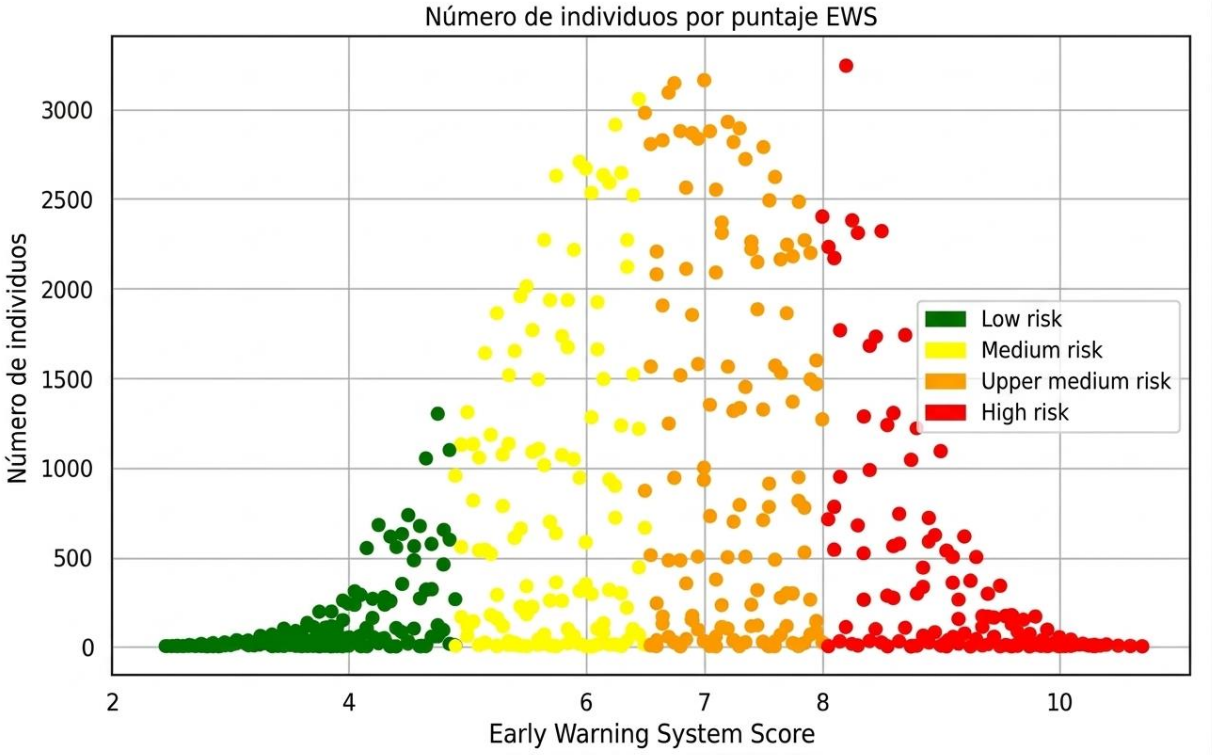
- This methodology allows us to capture the variability of the underlying variables more accurately and align the risk quantification with IRB regulatory standards.

Risk Category	Range
Low risk	X < 4.9
Medium risk	4.9 < X < 6.5
Upper-Medium risk	6.5 <X< 8.5
High risk	8 <X< 11

EWS developing

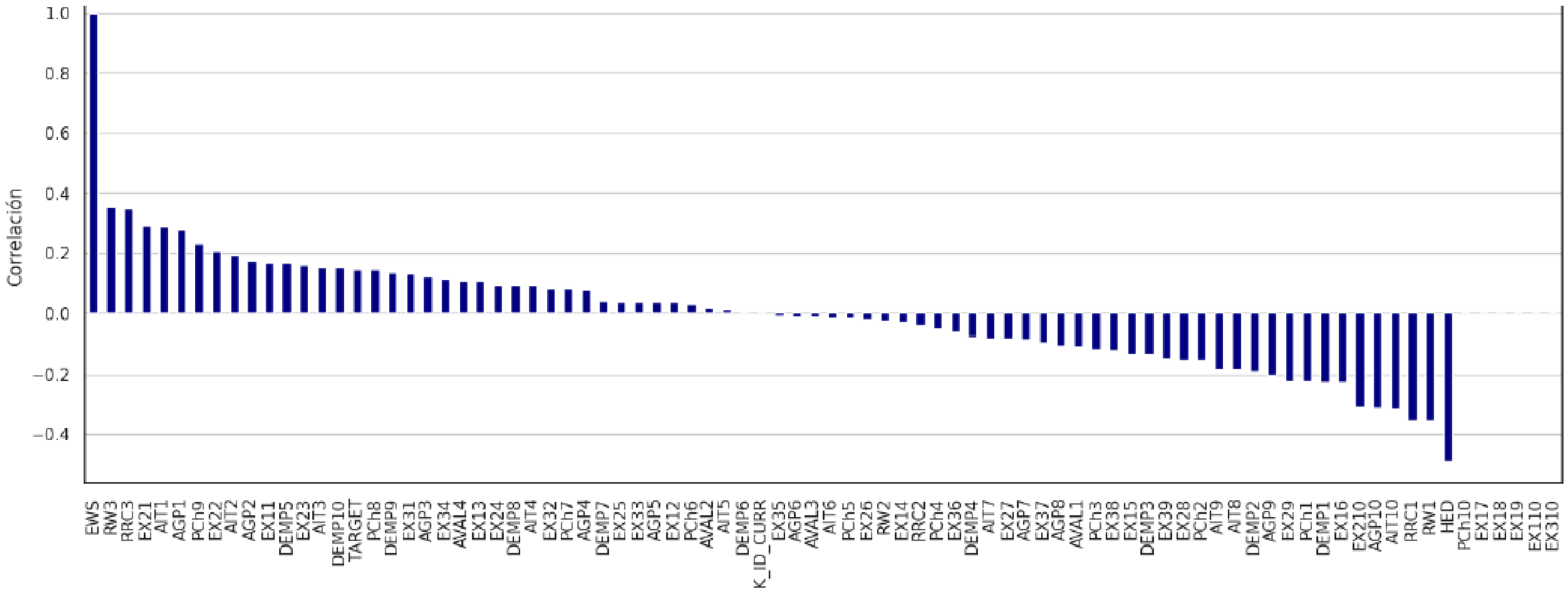
Risk Distribution





Relevant Variables

Imagen 33 - Correlación variables EWS



We use Gradient Boosting Models

- **xgboost**
- **catboost**

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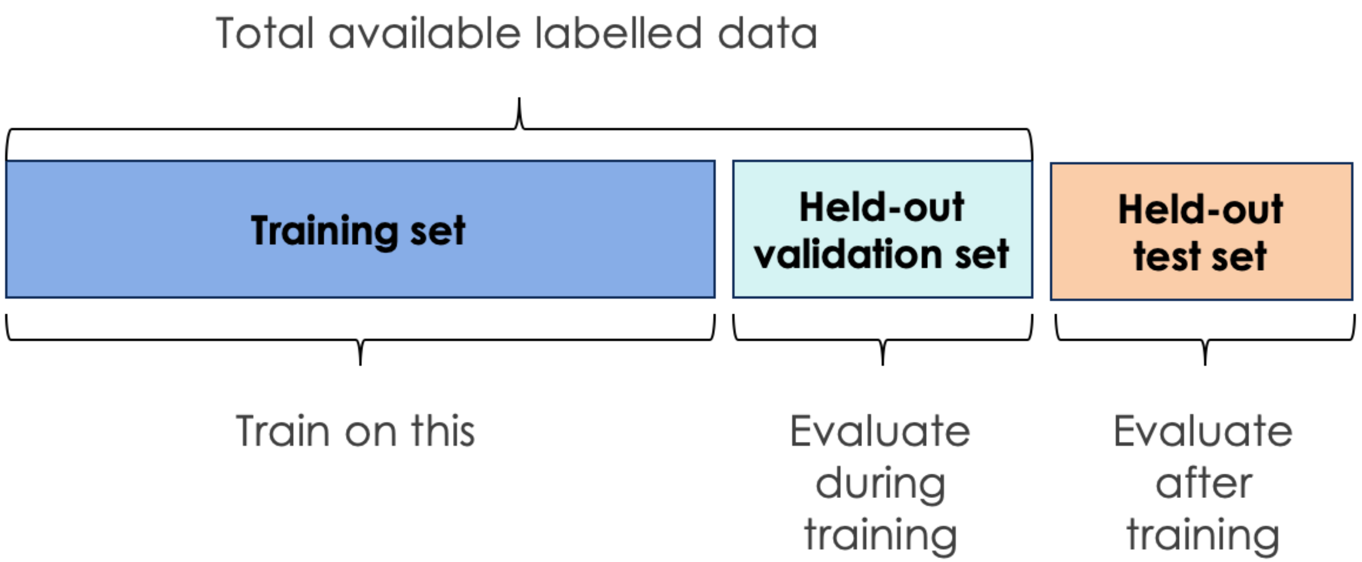
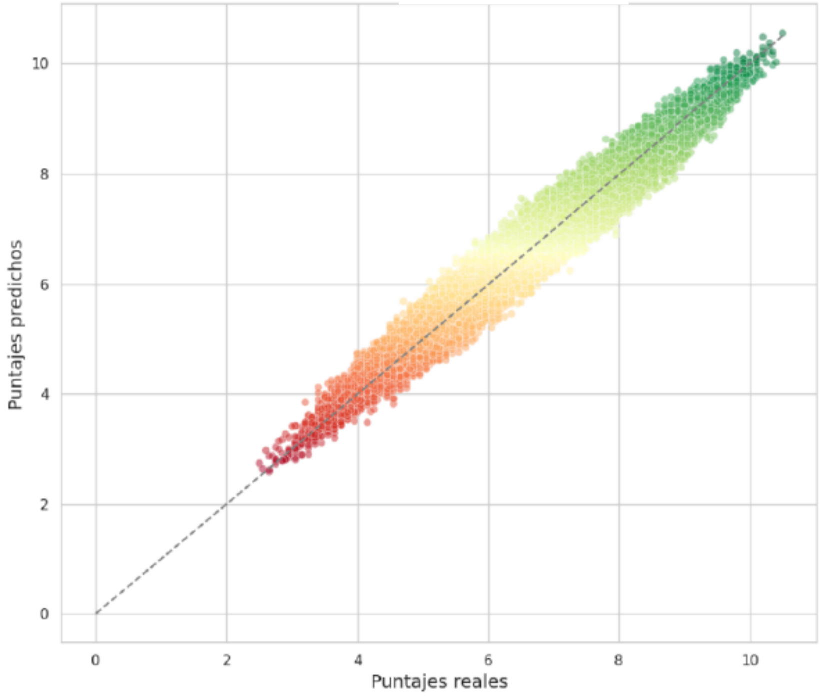


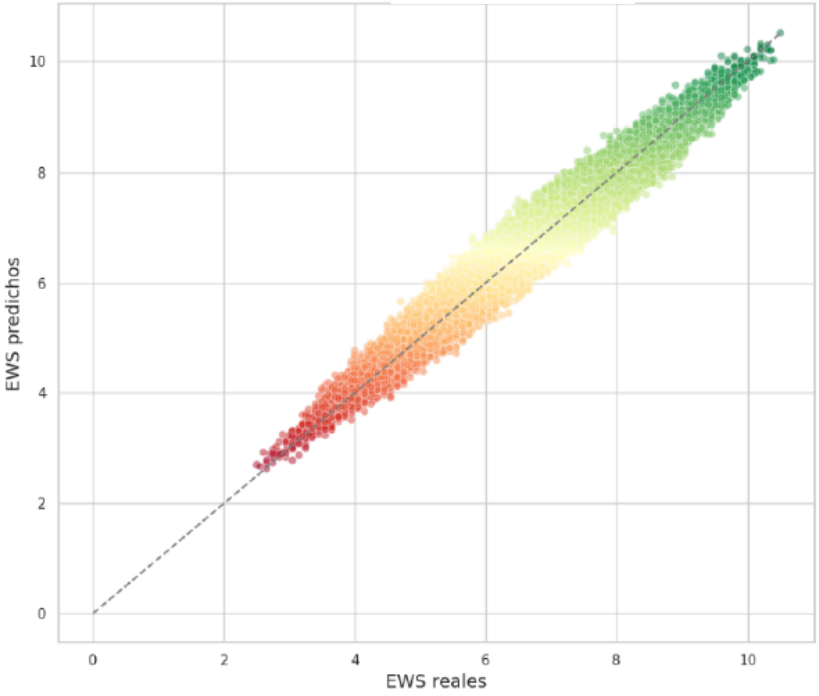
Expected Risk vs Predicted Risk

Yes! Now we use a Regression* ML approach

XGBoost



CatBoost



Fuente: Elaboración propia

METRIC	CatBoost	XGBoost
MAE	18,00%	18,80%
MSE	5,20%	5,60%
RMSE	23,10%	23,80%
Varianza	96,20%	95,90%

Regression approach, requires different performance metrics

The model predicts a continuous numerical value.

SHAP value and Relative Feature Importance

VARIABLE	SHAP VALUE
HED	
AVAL4	
AVAL1	
PCh9	
RW3	
AGP1	
EX11	
DEMP5	
AGP10	
EX21	

VARIABLE	IMPORTANCIA RELATIVA
MP10	1,53 %
Ch2	1,49 %

AI generates insights; the analyst makes the decisions.

- How m
  specific prediction.
- Explains each prediction individually
- Required by regulators
- Based on game theory

- The global importance of each variable across the entire model, rather than for an individual prediction.

Results

Is the Early Warning System aligned with the predicted rating and observed bank default behavior?

Risk Category	Low	Medium	Upper-Medium	High
Expected Default EWS	2,36%	4,43%	9,17%	14,80%
Predicted Default EWS	2,33%	4,35%	9,24%	15,28%

Risk Category	Low	Medium	Upper-Medium	High
Expected Non-Default EWS	97,64%	95,57%	90,83%	85,20%
Predicted Non-Default EWS	97,67%	95,65%	90,76%	84,72%

Results

Is the Early Warning System aligned with the predicted rating and observed bank default behavior?

Category	% Type I Error
Expected Default EWS	90,78%
Predicted Default EWS	84,72%

A **Type I** error leads to lost business...

Category	% Type II Error
Expected Default EWS	2,30%
Predicted Default EWS	4,35%

whereas **Type II** error implies additional capital consumption

Is This a Problem?

- According to **PwC & GALYTIX (2024), 8 out of 10 Early Warning System indicators are false positives.**

- Despite efforts to reduce this, banks often **do not allocate the majority of EWS improvement resources to this issue**.

- **Reason**: **A false positive means the client does pay,** which is the desired outcome.

The Real Problem for a Bank

- The true “pain point” is false negatives: **Clients classified as low risk who actually default**.

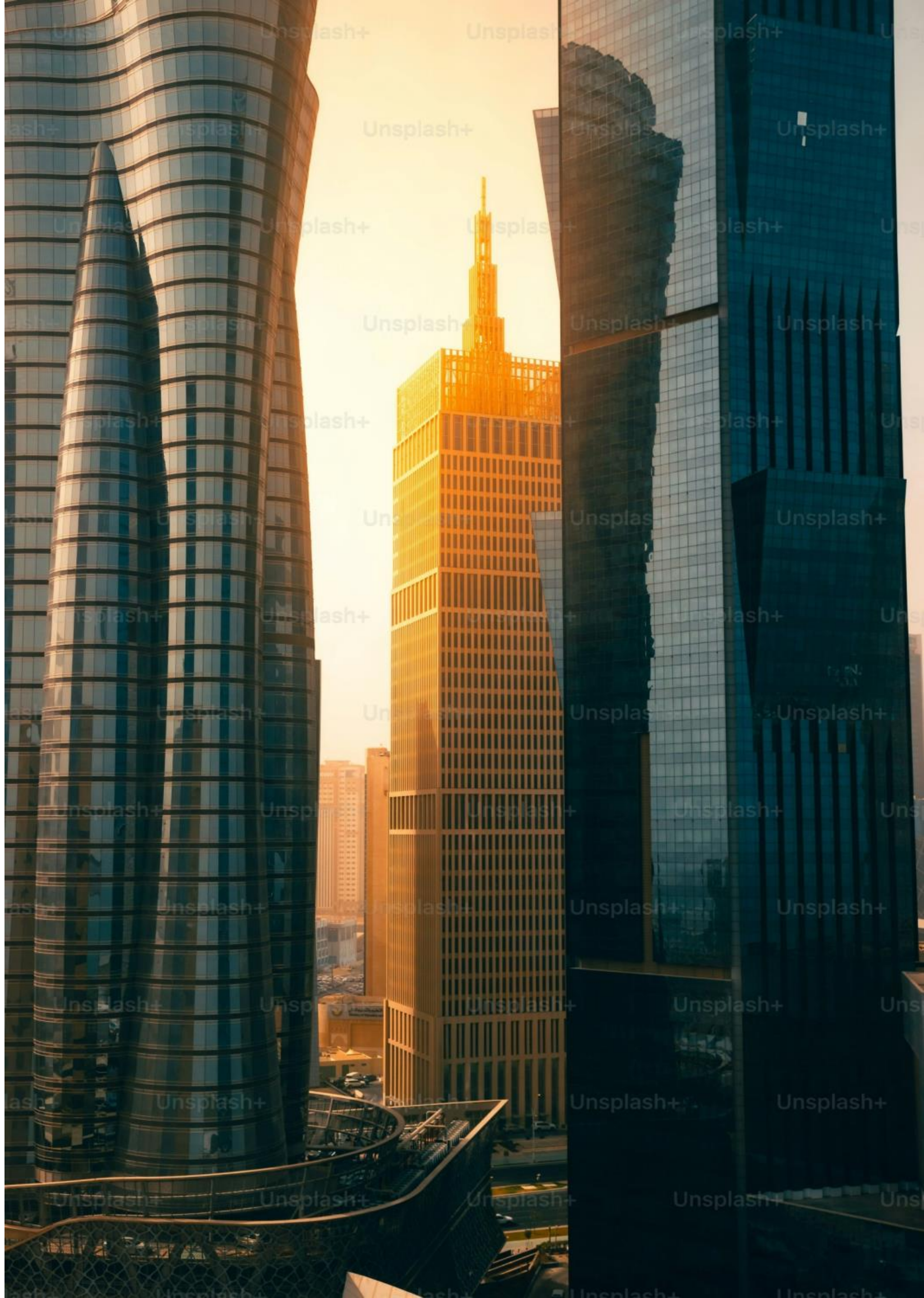
- These represent unexpected financial losses, which can affect:
  - Profitability
  - Capital planning
  - Portfolio stability

Why This Matters?

- Banks invest resources and capital based on the expectation of repayment.

- When clients unexpectedly default, losses erode expected returns.

- This highlights the need to **improve default-risk prediction**, especially for **low and moderate-risk segments.**



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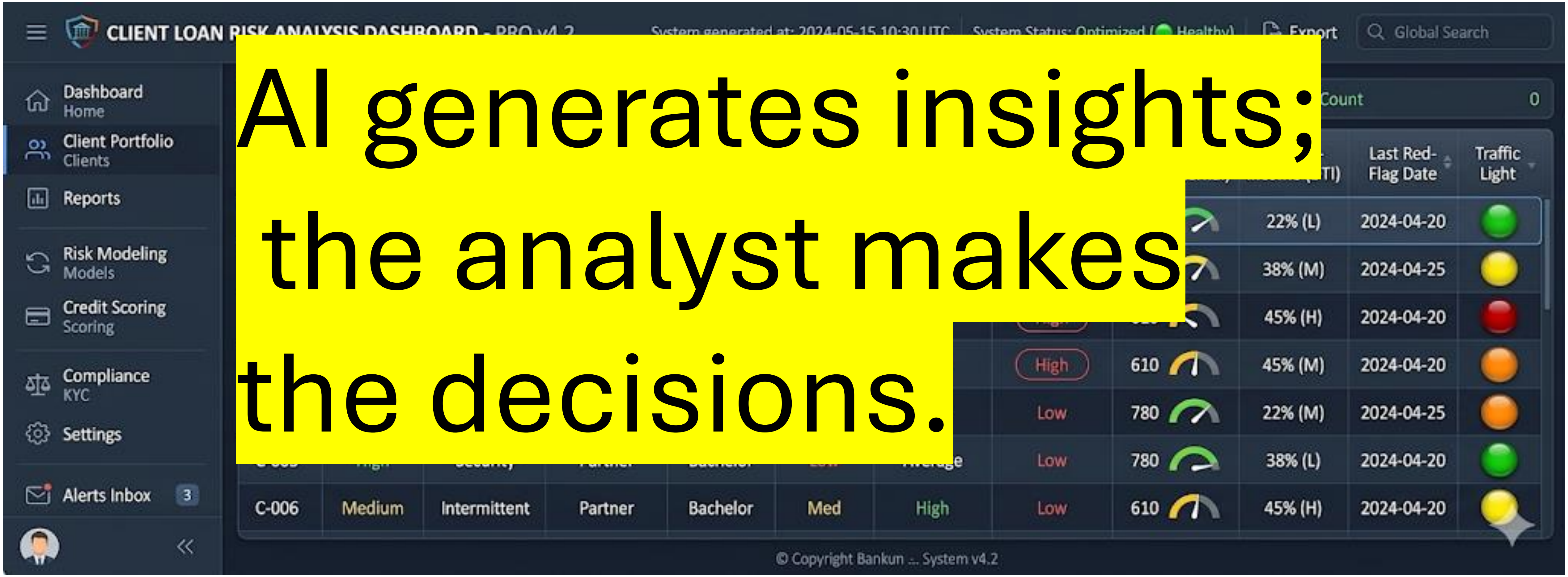
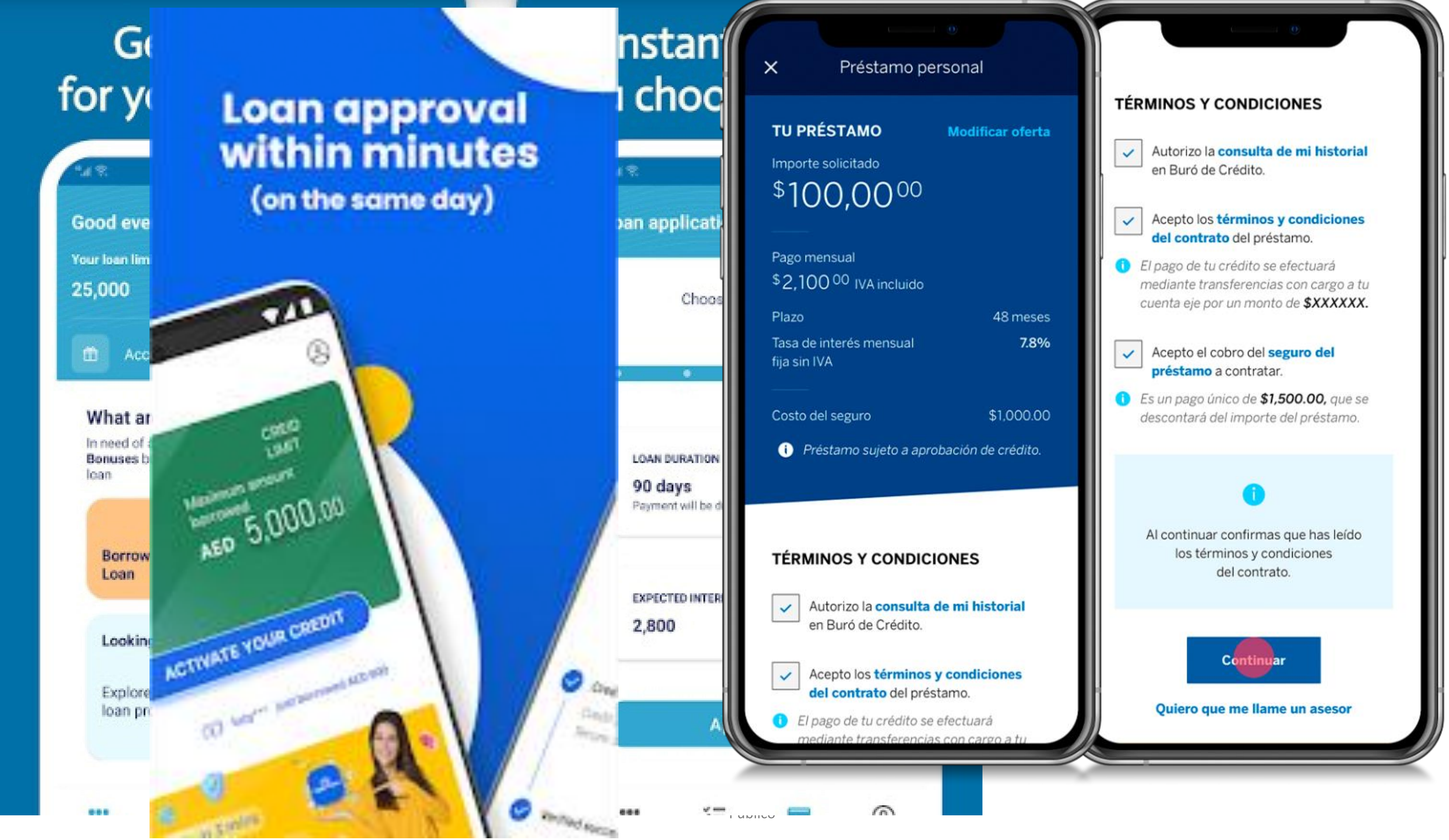
A EWS in the Real World

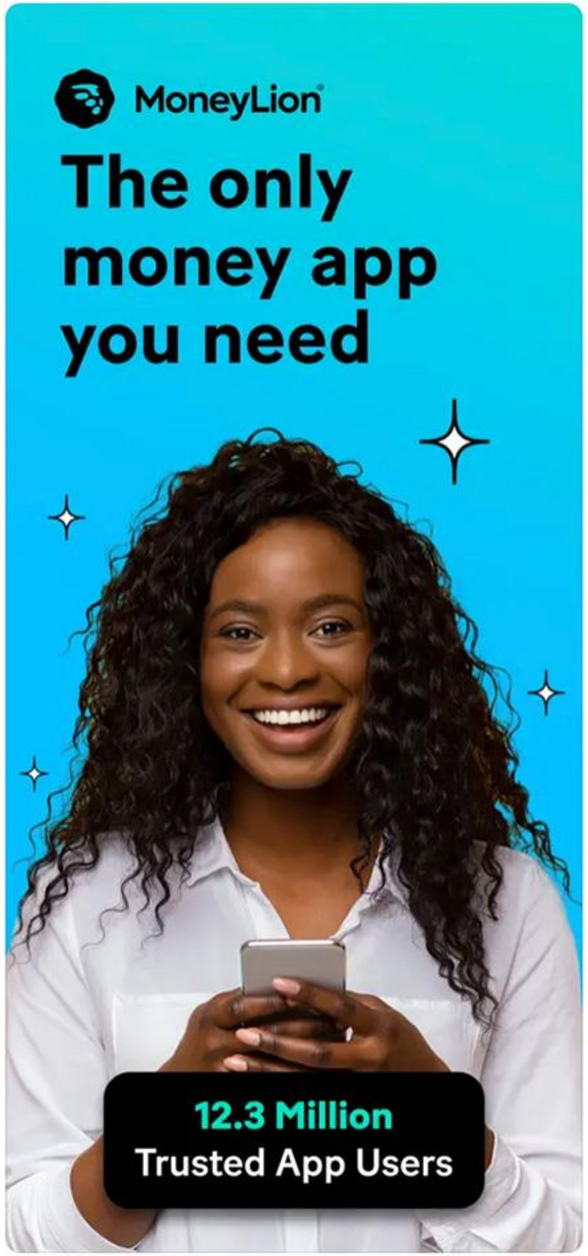
How a EWS usually look like at user level

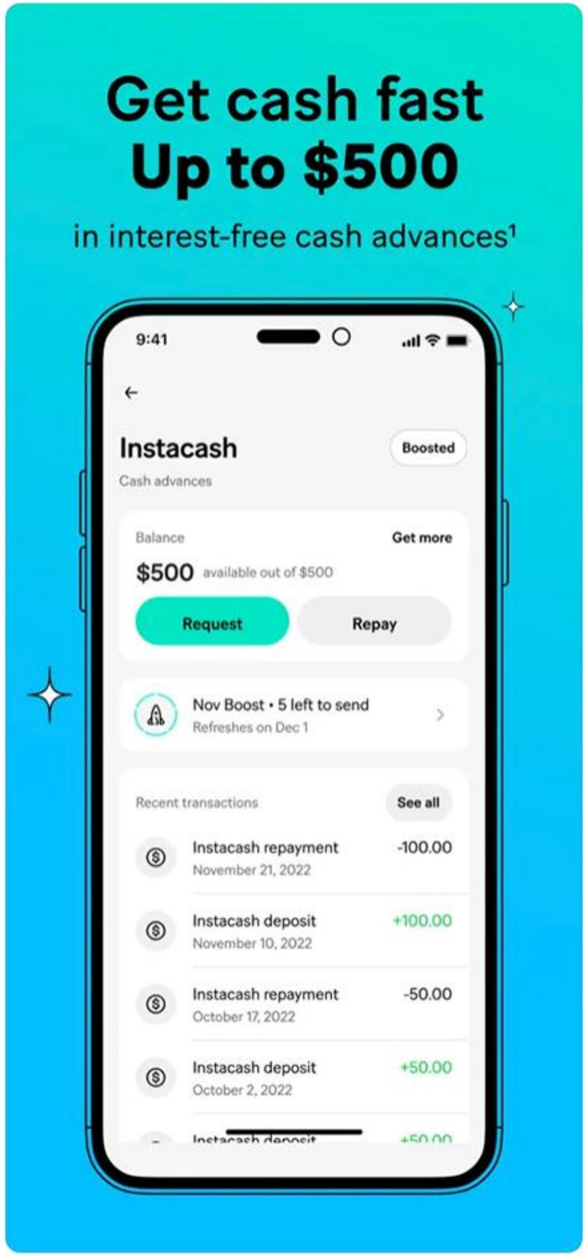


AI generates insights; the analyst makes the decisions.

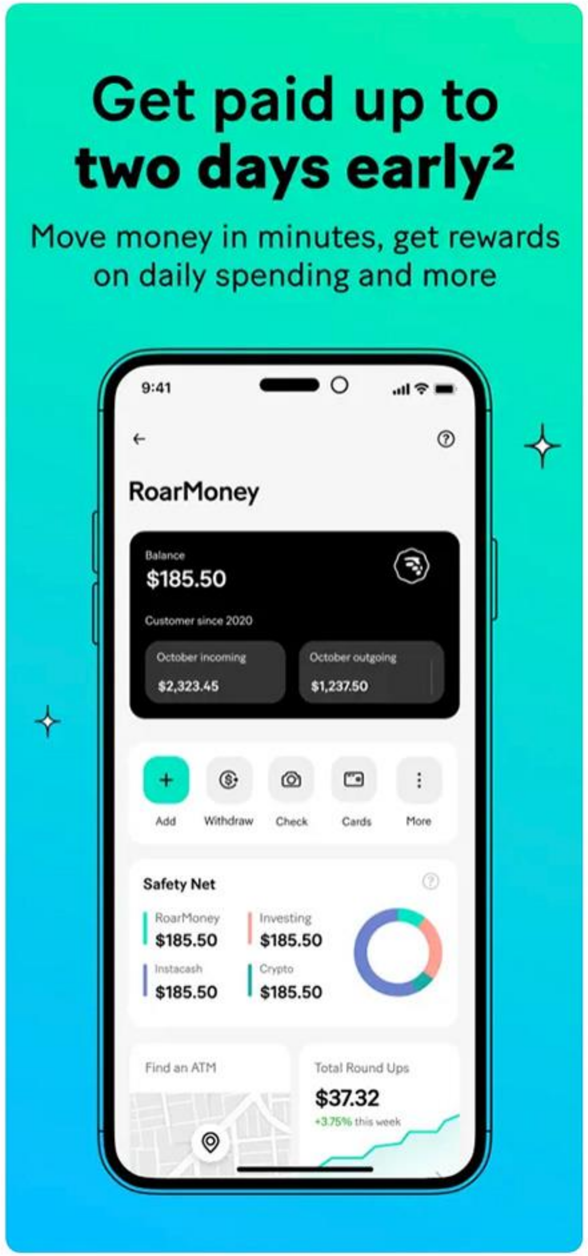


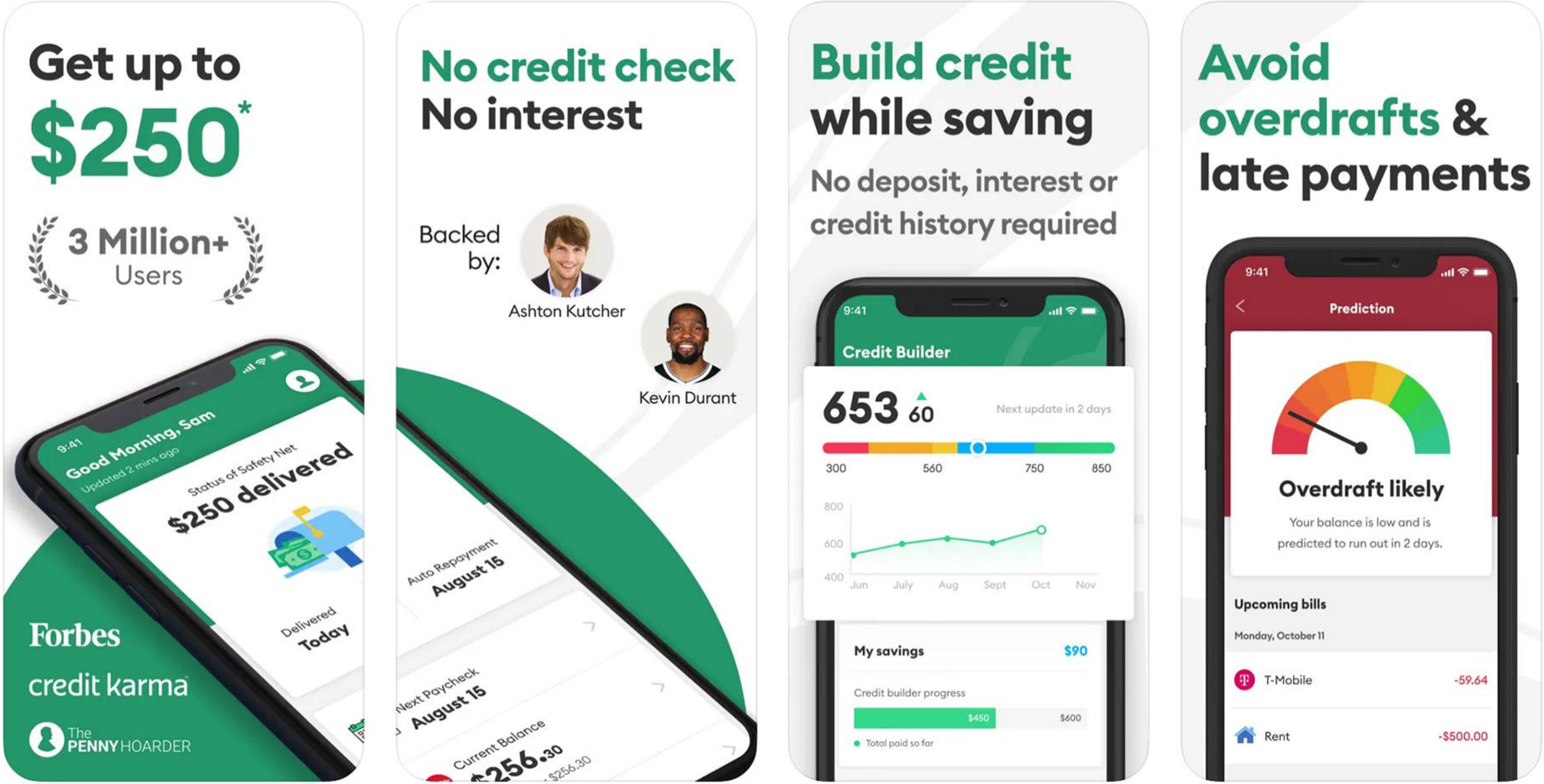
Loan approval within minutes
(on the same day)
CREDIT LIMIT
Maximum amount borrowed
AED 5,000.00
ACTIVATE YOUR CREDIT
Good eve
Your loan lim
25,000
LOAN DURATION
90 days
EXPECTED INTER
2,800
Préstamo personal
TU PRÉSTAMO
Modificar oferta
Importe solicitado
$100,00 00
Pago mensual
$2,100 00 IVA incluido
Plazo
48 meses
Tasa de interés mensual fija sin IVA
7.8%
Costo del seguro
$1,000.00
Préstamo sujeto a aprobación de crédito.
TÉRMINOS Y CONDICIONES
Autorizo la consulta de mi historial en Buró de Crédito.
Acepto los términos y condiciones del contrato del préstamo.
El pago de tu crédito se efectuará mediante transferencias con cargo a tu cuenta eje por un monto de $XXXXXX.
Acepto el cobro del seguro del préstamo a contratar.
Es un pago único de $1,500.00, que se descontará del importe del préstamo.
Al continuar confirmas que has leído los términos y condiciones del contrato.
Continuar
Quiero que me llame un asesor


MoneyLion
The only money app you need
12.3 Million
Trusted App Users


Get cash fast
Up to $500
in interest-free cash advances¹
9:41
Instacash
Boosted
Cash advances
Balance
Get more
$500 available out of $500
Request
Repay
Nov Boost • 5 left to send
Refreshes on Dec 1
Recent transactions
See all
Instacash repayment
November 21, 2022
-100.00
Instacash deposit
November 10, 2022
+100.00
Instacash repayment
October 17, 2022
-50.00
Instacash deposit
October 2, 2022
+50.00


Make smart money decisions
Tips, personalized insights, & plans
9:41
Discover
Trending
Playlist
@diavante.brown
How To Beat Inflation


Get paid up to two days early²
Move money in minutes, get rewards on daily spending and more
9:41
RoarMoney
Balance
$185.50
Customer since 2020
October incoming
$2,323.45
October outgoing
$1,237.50
Add
Withdraw
Check
Cards
More
Safety Net
RoarMoney
$185.50
Investing
$185.50
Instacash
$185.50
Crypto
$185.50
Find an ATM
Total Round Ups
$37.32
+3.75% this week


Get up to
$250*
3 Million+
Users
9:41
Good Morning, Sam
Updated 2 mins ago
Status of Safety Net
$250 delivered
Delivered
Today
Forbes
credit karma
The PENNY HOARDER
No credit check
No interest
Backed by:
Ashton Kutcher
Kevin Durant
Auto Repayment
August 15
Next Paycheck
August 15
Current Balance
$256.30
Build credit
while saving
No deposit, interest or
credit history required
9:41
Credit Builder
653 60
Next update in 2 days
300
560
750
850
800
600
400
Jun
July
Aug
Sept
Oct
Nov
My savings
$90
Credit builder progress
$450
$600
Total paid so far
Avoid
overdrafts &
late payments
9:41
Prediction
Overdraft likely
Your balance is low and is
predicted to run out in 2 days.
Upcoming bills
Monday, October 11
T-Mobile
-59.64
Rent
-$500.00

Practical Implications

- Early intervention
- Capital optimization
- New business opportunities
- Improved credit monitoring

Challenges & Future Works

Challenges & Future Works

- Continuous manage of relevant variables
- Recalibration of the classification thresholds
- Use more advanced modeling techniques
- Refine the Early Warning System to better identify true risk signals

- We are looking forward:
  - Integration with Basel IV
  - Agentic AI for data collection

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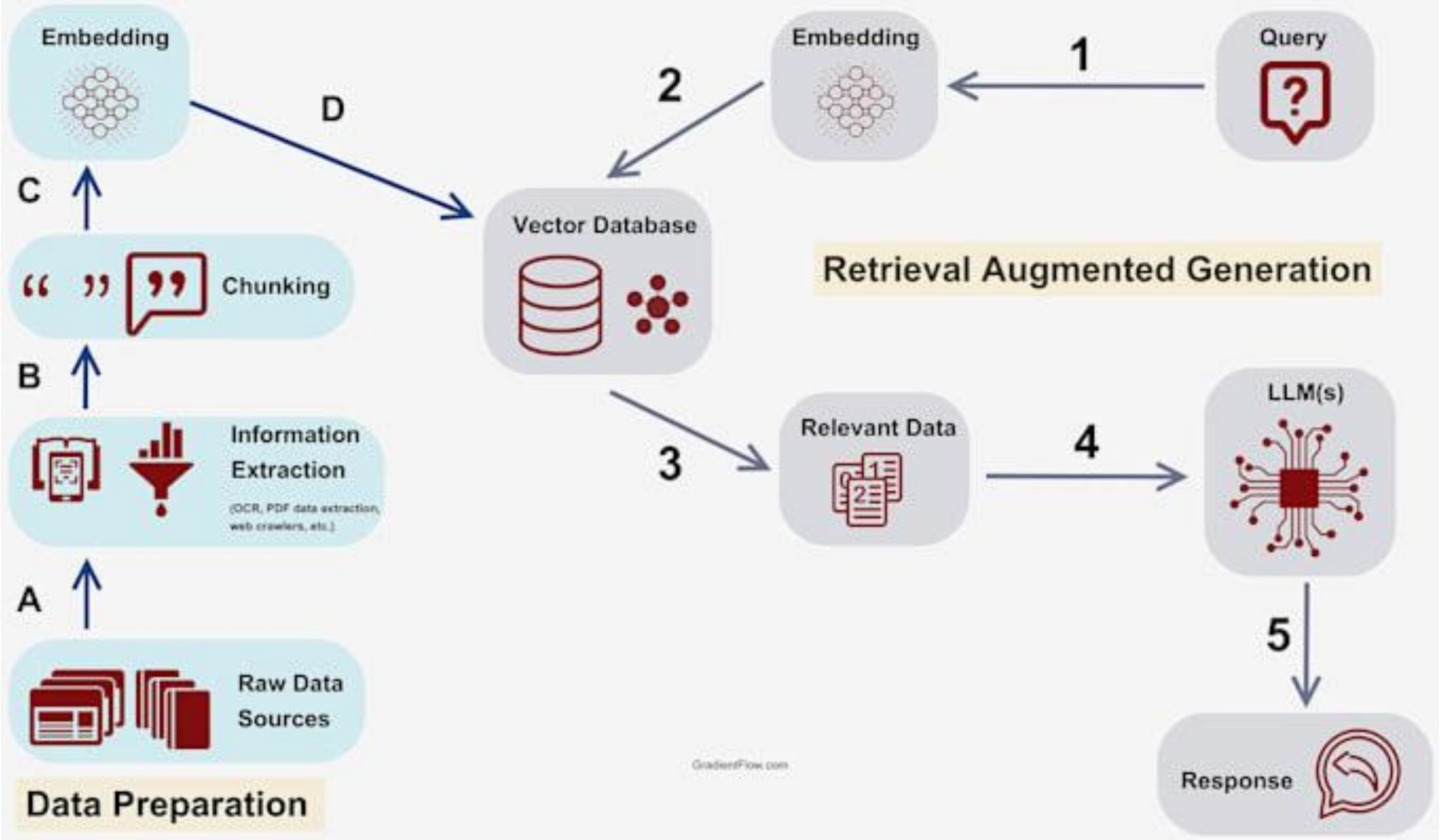
Agentic AI for Data Collection



Contact

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