

Interpretable credit risk modelling with quantum-inspired algorithms

Samuel Fernández Lorenzo



**DIGITAL REPORTING IN
EUROPE**

3–5 JUNE 2025, FRANKFURT

Hosted by the European Central Bank



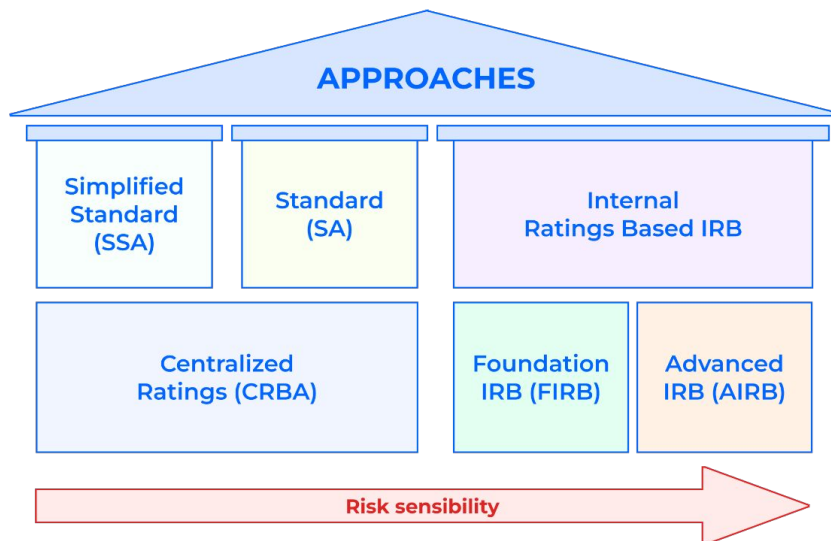
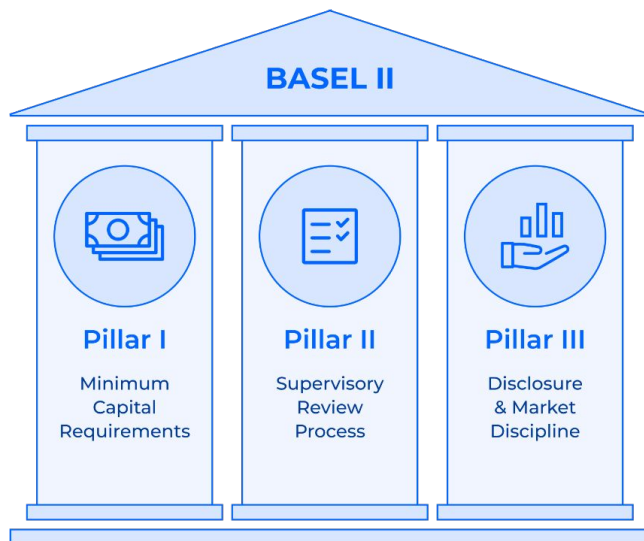
XBRL | EUROPE

About me



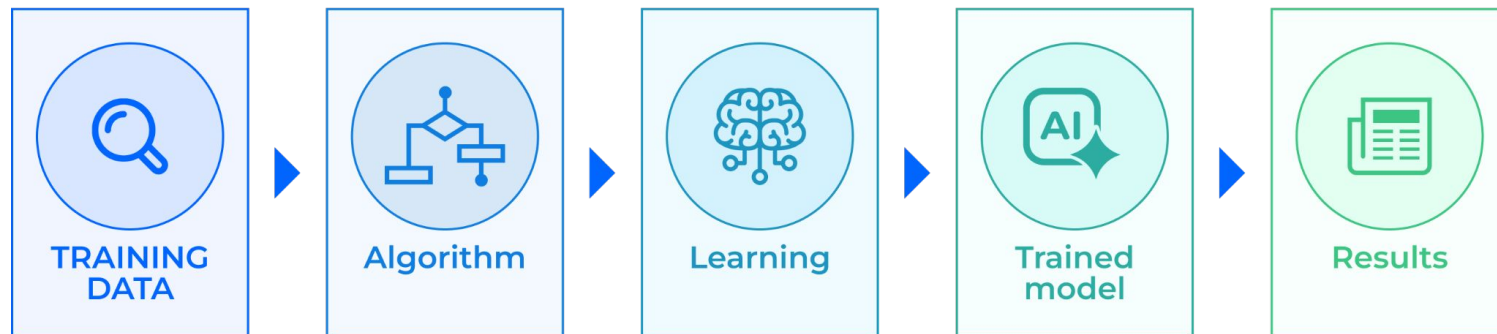
- Co-founder/CEO at Inspiration-Q
- PhD in quantum physics
- Associate professor at IE University

Credit risk modeling

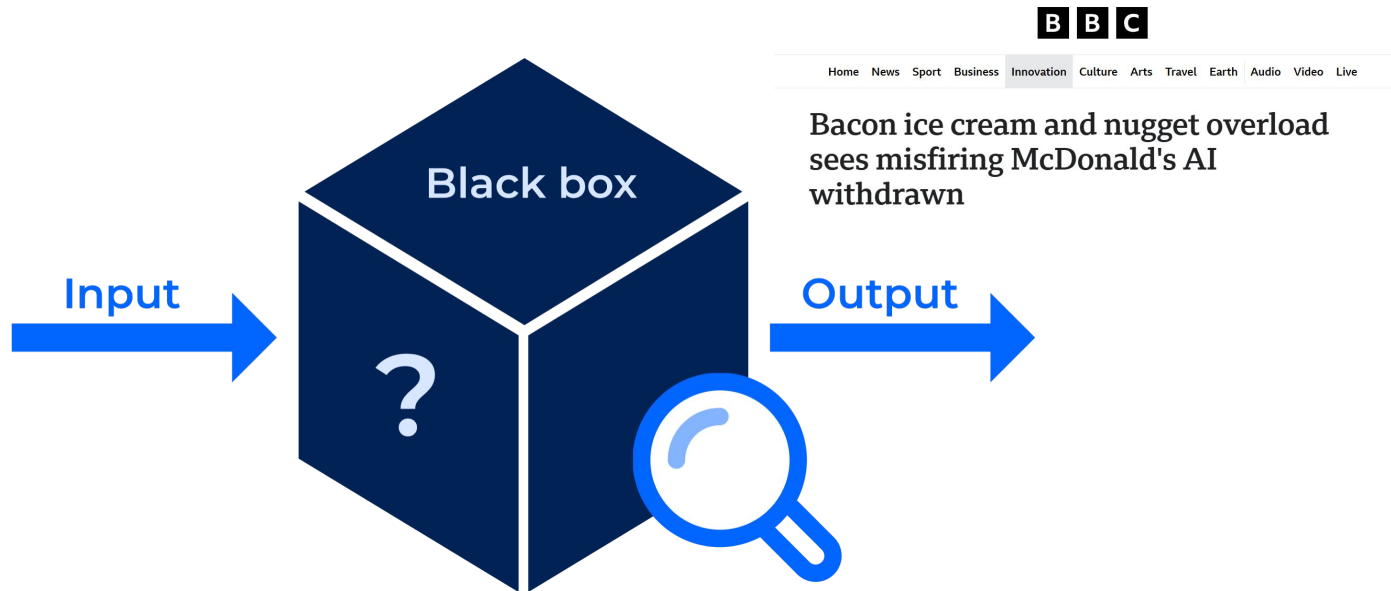


Solution: Machine Learning

Machine Learning Process



A new problem arises: lack of interpretability



What makes a good interpretable model?

1. As **concise** as possible
2. Formulated in terms of **basic logic rules** (and, or, ...)
3. Formulated in terms of **linear** operations

Basic interpretable model: logistic regression

Example

	beta	exp(beta)
feature_name		
intercept	-2.806086	0.060441
age	-0.379303	0.684338
Number Of Time 30-59 Days Past Due Not Worse	1.736287	5.676227
Monthly Income	-0.721586	0.485981
Number Of Times 90 Days Late	1.484934	4.414676
Number Real Estate Loans Or Lines	0.090145	1.094333
Number Of Time 60-89 Days Past Due Not Worse	-3.055844	0.047083
Number Of Dependents	0.120262	1.127793

$$\ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k$$

Odds ratio

P: probability of default

X_k: Feature k

Problem: **linearity limits accuracy**

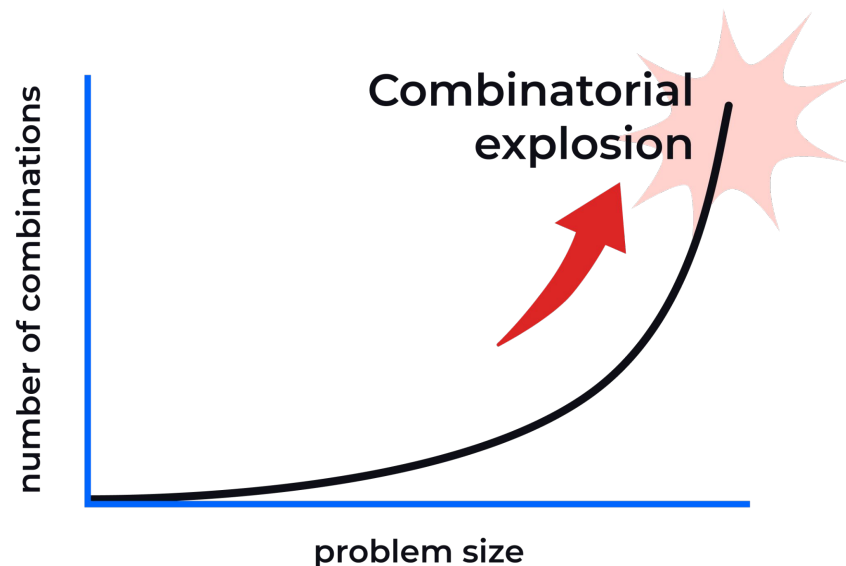
Feature selection, a key difficult problem

Use **less features** if possible to improve **conciseness** and **performance**

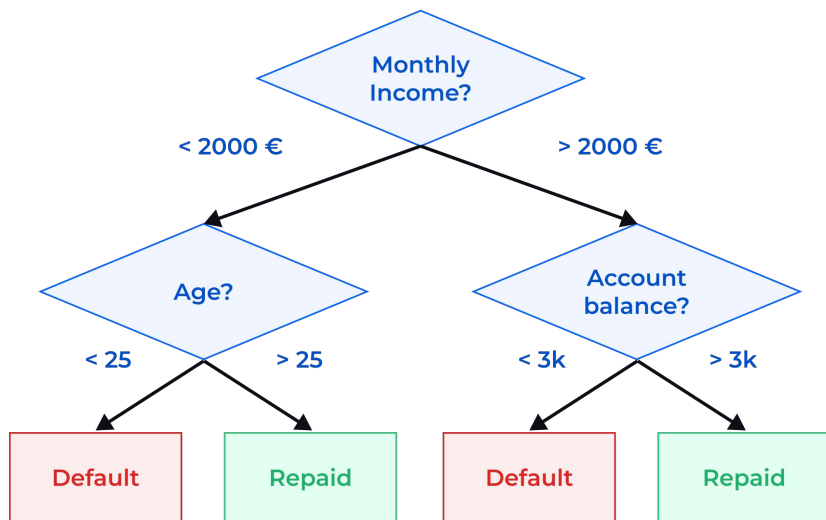
Choose a basket of **20** features **out of 100** to create a logistic regression with the **best performance**?

535,983,370,403,809,682,970 combinations to explore

Exponential combinatorial problem intractable with conventional solvers.



Another interpretable model: decision tree



Tree depth ~ Conciseness

Key advantage: a **decision tree** implicitly introduces non-linearity!

Building improved interpretable models

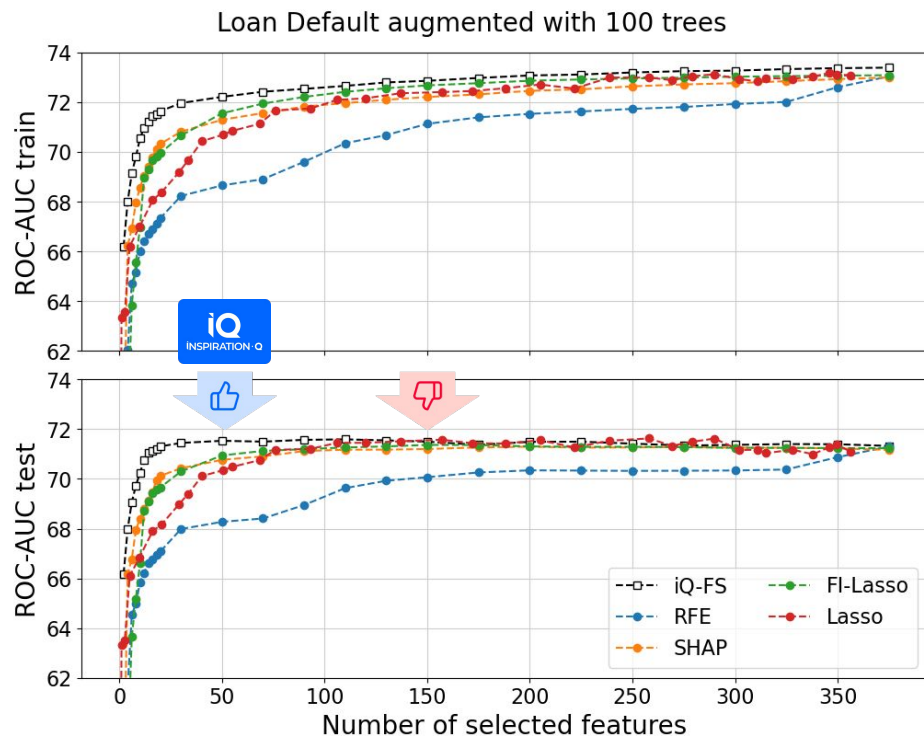


1. Add new candidate **non-linear interpretable** features using **short decision trees**
2. Apply **feature selection** on the **expanded dataset** to choose the best basket.

Example

Feature	β_i	e^{β_i}
Intercept	-1.7	0.2
Number Of Open Credit Lines And Loans	0.025	1.025
Age > 54 and Debt Ratio > 0.563	0.46	1.59
Age ≤ 54 and Times 60–89 Days Past ≡ 0	-1.19	0.30
Age > 54 and Times 60–89 Days Past ≡ 0	-1.43	0.24
Age ≤ 54 and Times 90 Days Late ≡ 0	-1.56	0.21
Age > 54 and Times 90 Days Late ≡ 0	-1.93	0.15
Times 30–59 Days Past ≡ 1	-0.46	0.63
Times 60–89 Days Past ≡ 0 and Times 30–59 Days Past > 0	0.71	2.0
Times 60–89 Days Past ≡ 0 and Revolving Utilization > 0.698	0.42	1.52
Times 90 Days Late ≡ 0 and Times 60–89 Days Past ≡ 0	-0.59	0.56
Times 90 Days Late ≡ 0 and Times 30–59 Days Past > 0	0.71	2.0
Times 90 Days Late > 1	0.67	2.0
Times 90 Days Late ≡ 0 and Revolving Utilization > 0.548	0.54	1.71
Times 90 Days Late ≡ 0 and Number Real Estate Loans Or Lines > 4	1.1	3.0
Revolving Utilization > 1.004	0.63	1.9
Revolving Utilization ≤ 0.314	-0.60	0.55

Quantum-inspired algorithms for feature selection



We need powerful **feature selection algorithms** for the previous idea to work well. **Quantum-inspired algorithms** significantly **outperform** conventional methods.

Same performance using 100 less features!!

Conclusions: 3 key ideas



New type of interpretable model to close the gap in performance with black-box models

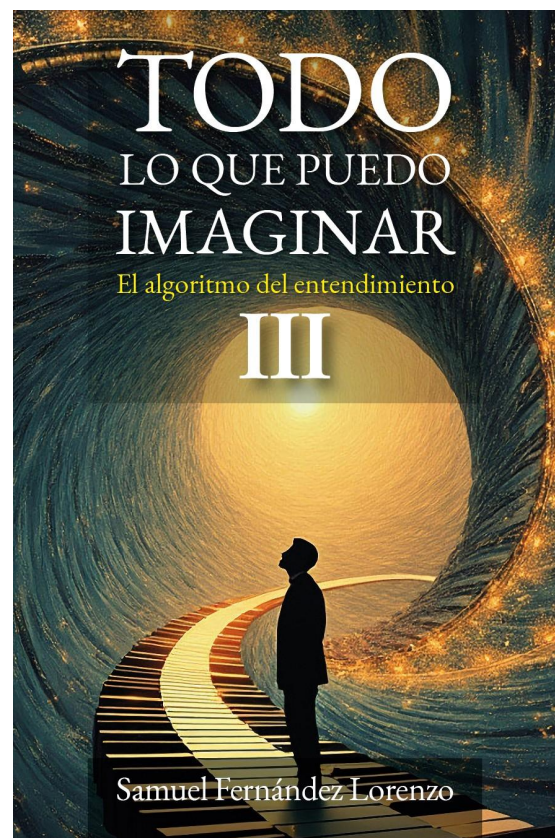


Powerful **feature selection** techniques are key for the previous idea to work.



Quantum-inspired feature selection offers a unique approach to build interpretable models with state-of-the-art performance.

Books



Thanks for your attention

DIGITAL REPORTING IN EUROPE

3-5 JUNE 2025, FRANKFURT

Hosted by the European Central Bank



XBRL | **EUROPE**