

# Turning Invoices into Credit Signal

## Multimodal AI to Predict Brazilian Invoice Defaults

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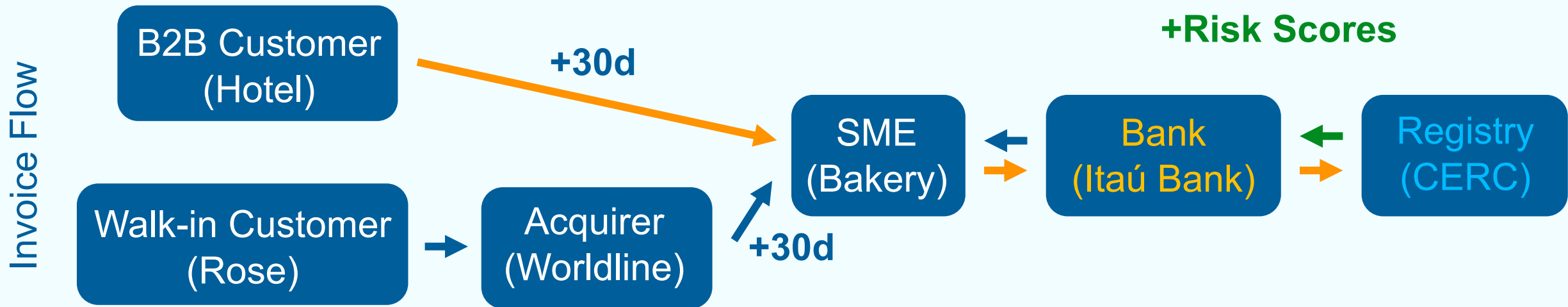
Rose  
Dana



Lottie  
Schulte-Bockum

### Problem Statement

CERC is Brazil's leading data infrastructure for banks and credit funds to register SMEs' (Small and Medium-sized Enterprises) invoices as receivables for credit access.



**Problem:** Banks currently rely on company-level heuristics to distribute credit but have no historical insights on invoice behavior. This means SMEs receive limited credit access at high interest rates.

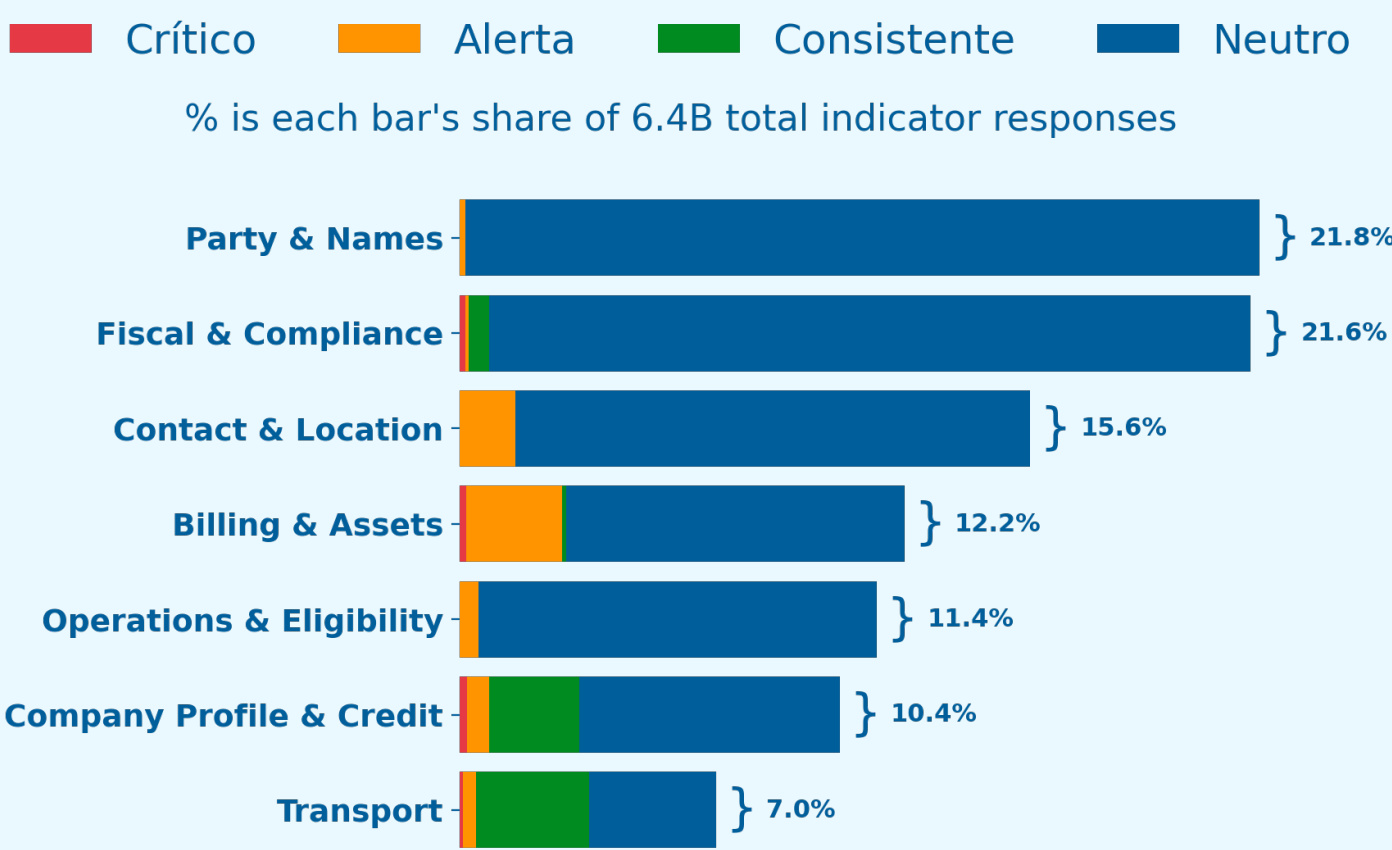
### Objective

**Build Risk Scores:** Leverage **Invoice-level** data that CERC assesses to produce default risk scores to help **Banks** score credit.

### CERC's Invoice Assessments

CERC runs ~200 automated health & fraud checks for every registered invoice, verifying the parties, fiscal documents, transport events and billing data.

#### Health Assessment Indicator Response Distribution



Each indicator returns a natural-language message, e.g.:

- Crítico → "CT-e cancelado"
- Critical → "Transport e-document cancelled"

### Data Engineering

#### 1. Credit Transactions

- Rev. past 7/30/60/90d
- Rev. Velocity
- Rev. Acceleration
- Rev. Stability
- Projected Rev.

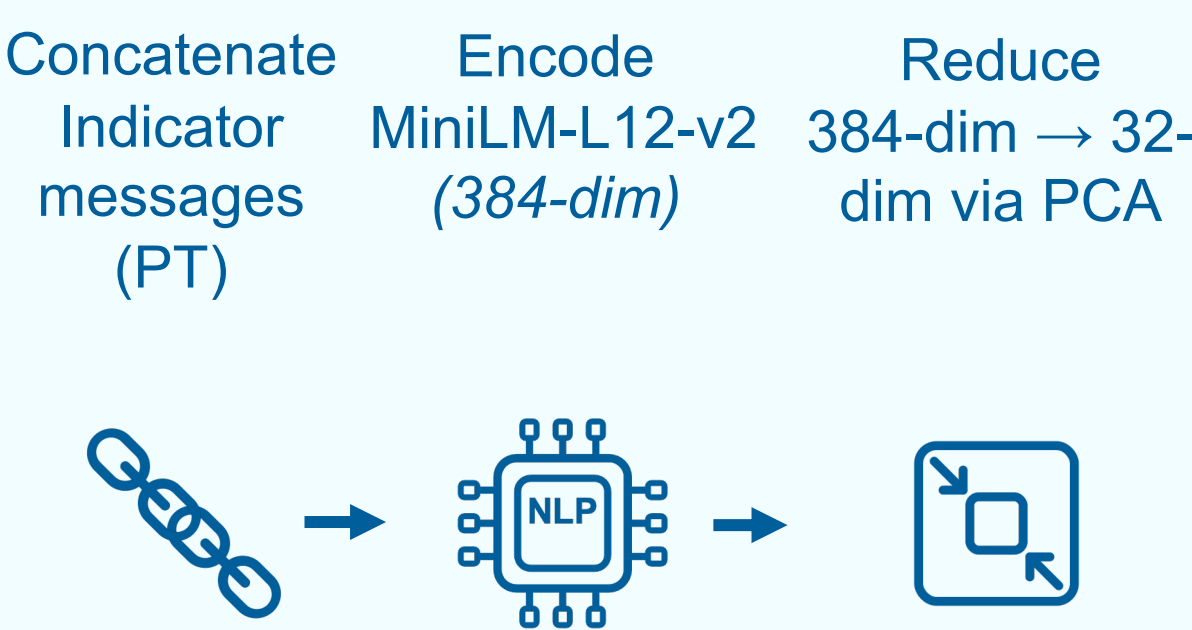


#### 2. Payer-Payee Network

Historic relationships between payers & payees  
e.g. Closed Loop (A sells to B sells to C sells to A)



#### 3. Indicator Response Embeddings



### Methodology

No ground-truth default label exists, so we built two independent proxies

#### 1. Engineered Features

- 1. Credit Transactions
- 2. Payer-Payee Network
- 3. Indicator Response Embeddings

#### 2. Proxy Target Definition

##### Proxy 1: Repeated Relationship

When a new invoice is issued after the installment's due date

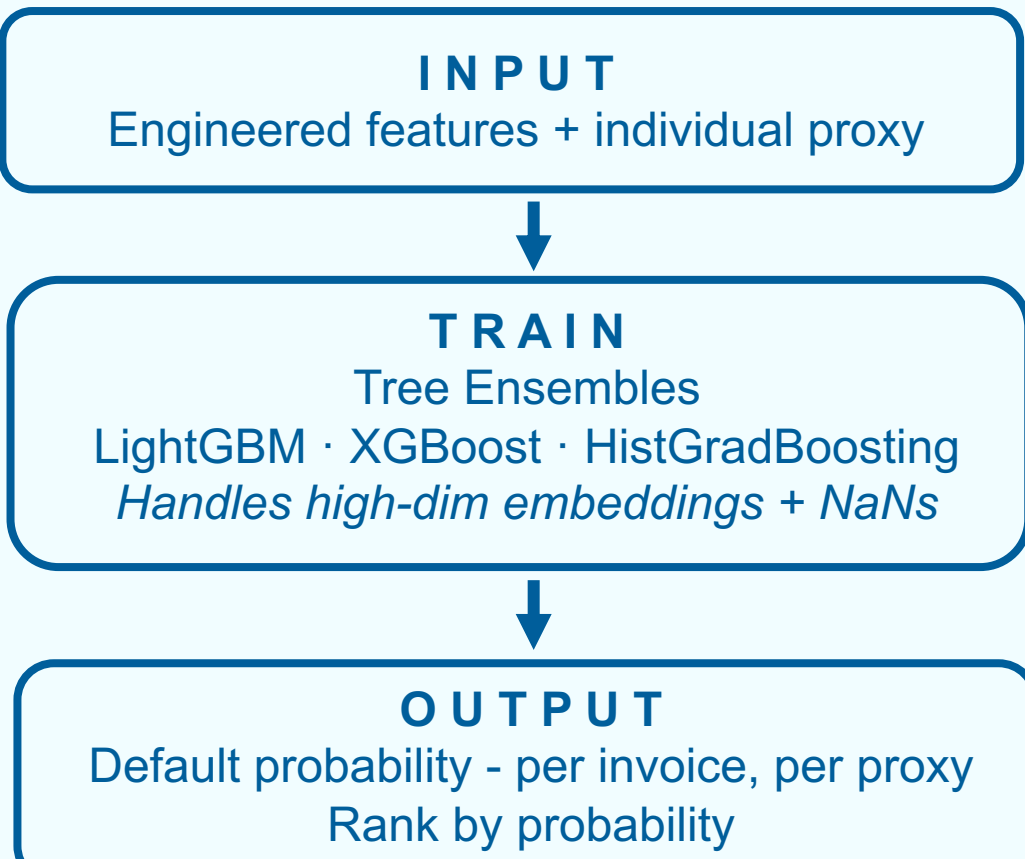


##### Proxy 2: Critical Indicator Change

When an invoice is reviewed at a later date and at least one indicator changes to Critical



#### 3. Modeling Approach



#### 4. Proxy Verification

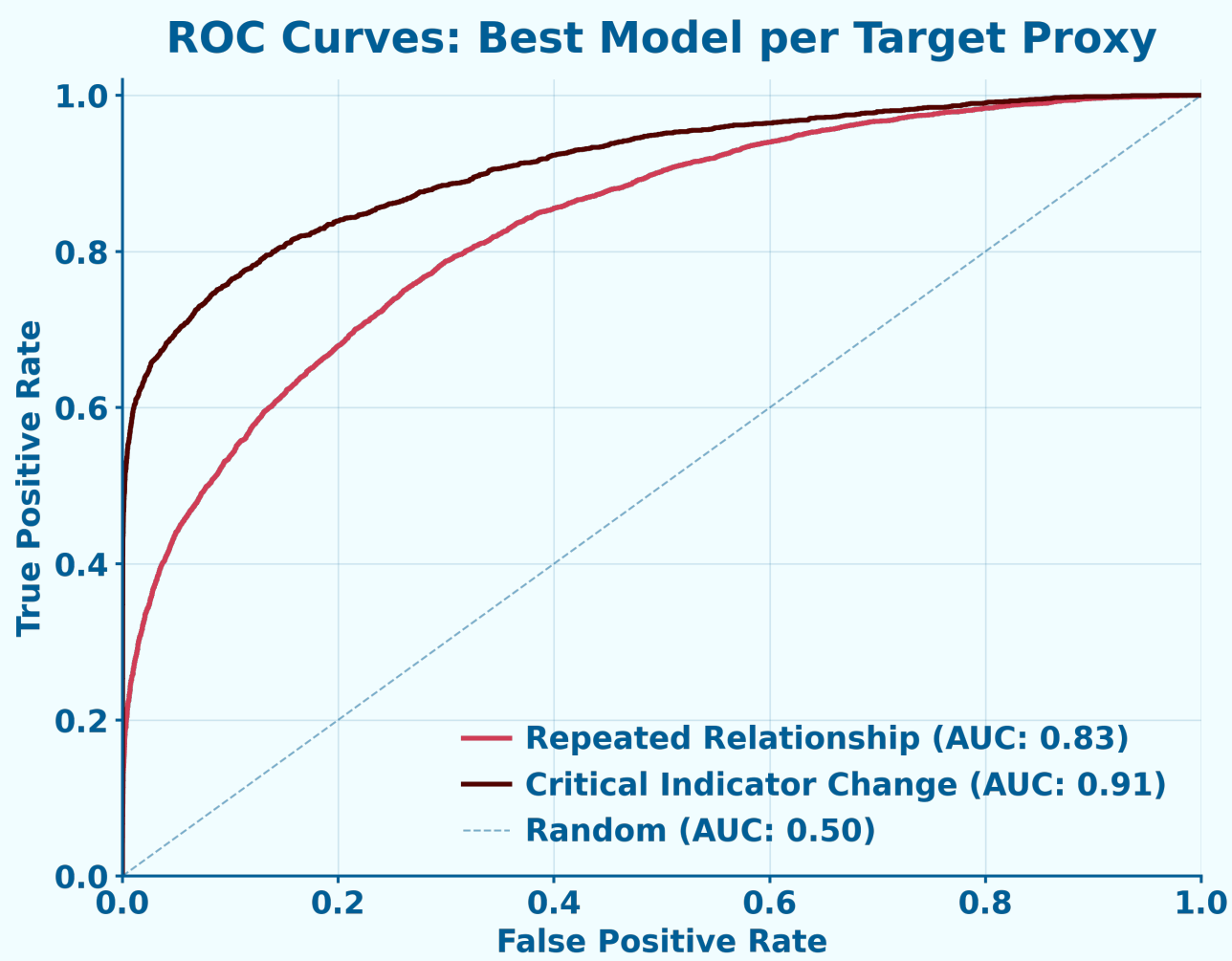
Spearman's  $\rho$  = Pearson correlation applied to the ranks of the two models' predictions.

Captures whether they order invoices by risk consistently, ignoring the raw probability scale.

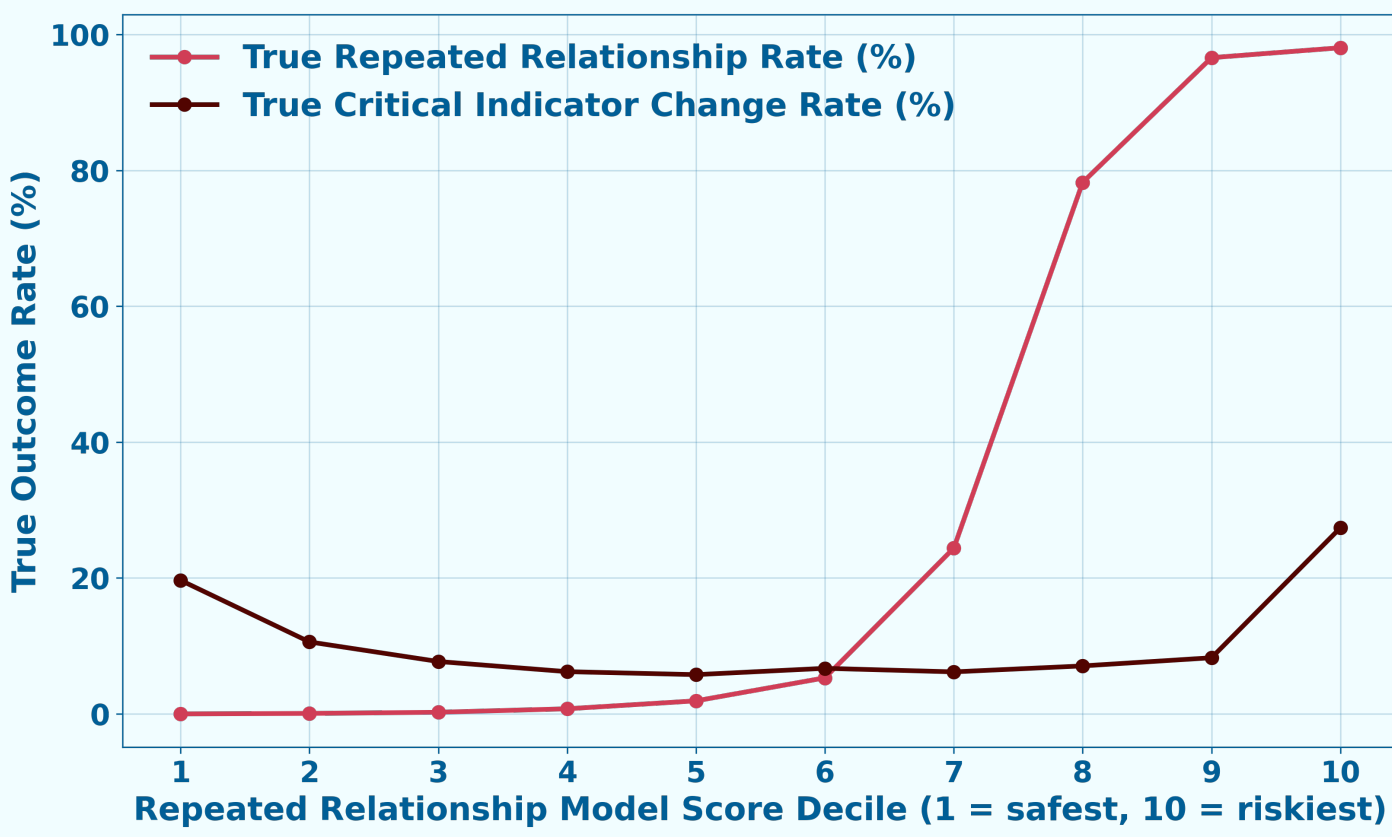
$$\rho_s = \frac{\sum_i (R(x_i) - \bar{R}_x) (R(y_i) - \bar{R}_y)}{\sqrt{\sum_i (R(x_i) - \bar{R}_x)^2 \cdot \sum_i (R(y_i) - \bar{R}_y)^2}}$$

$x, y$  = invoice ranks under Proxy 1 & 2  
 $\bar{R}_x, \bar{R}_y$  = mean ranks  
 $\rho \in [-1, 1]$ , higher = stronger agreement

### Results



#### True Positive Rate of Each Proxy Target by Repeated Relationship Score Decile



$$\rho_s = 0.202$$

**Interpretation:** The two proxies define default differently and flag largely different invoices, so the choice of proxy depends on the business context.

### Business Impact

#### Market Risk



5% of CERC's R\$250B (US\$50B) invoice market defaults annually.

#### SMEs Impacted



3.5M  
70% of Brazil's 5M SMEs are denied credit access. Using invoice signals will allow 3.5M SMEs to be considered.

#### Solution



Production-ready proxy-based ML Engine.

#### Value at Stake



\$1.7B  
With a recall of 0.694, our proxy-based model can catch up to R\$8.7B (US\$1.7B) annually.

### CERC's Future

**Duplicata Escritural:** Regulation requiring all invoices to be registered digitally alongside payment information, bringing the true target variable to CERC in the long term.

