

Balancing Risk and Profit: Predicting the Performance of Potential New Customers in the Insurance Industry

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About me



Celia Osorio

2022 •



2023 •



Present •



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1. The Challenge of Predicting New Customers' Performance

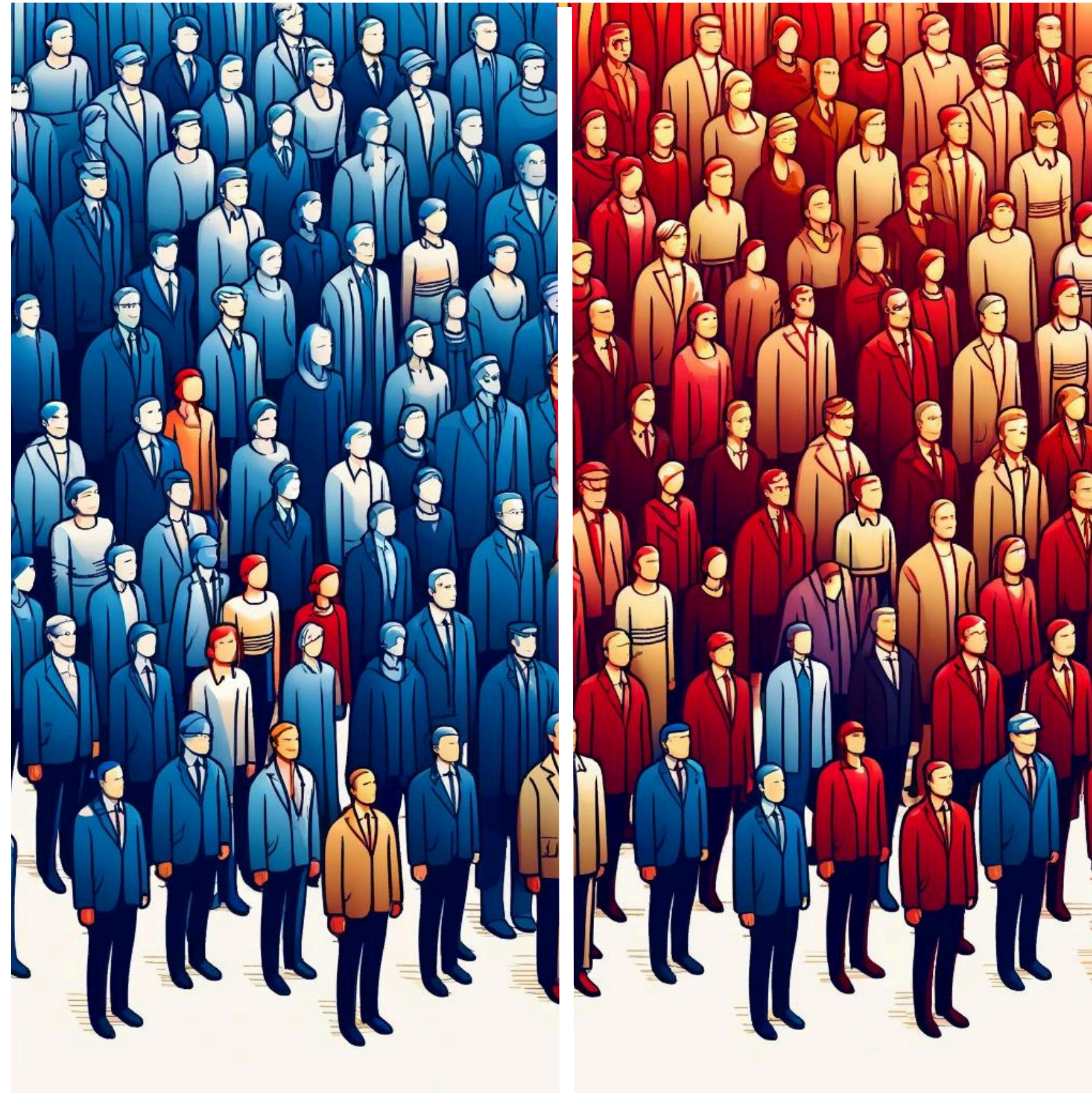
The Challenge of Predicting New Customers' Performance



With limited data, can we predict with confidence how new clients will perform in the company?

2. Objective of the Study

TARGET: Average Annual Profit (AAP)



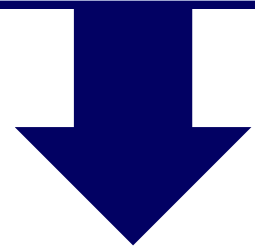
$$AAP > 0$$



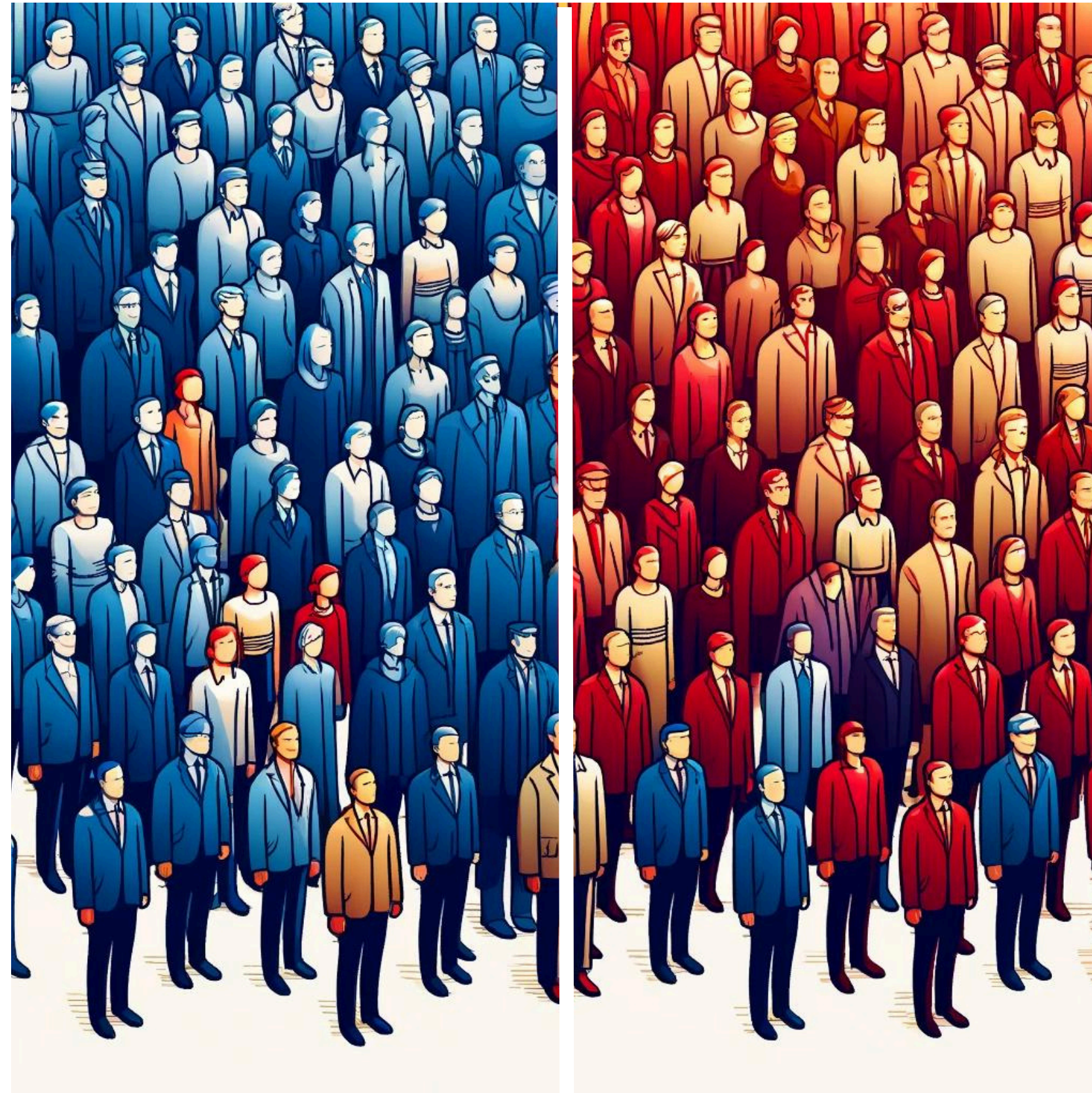
TARGET: Average Annual Profit (AAP)

**High-
performance
Customer**

Group 0



*Customer to be **accepted***



$AAP > 0$



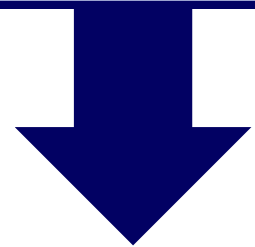
TARGET: Average Annual Profit (AAP)

$AAP \leq 0$

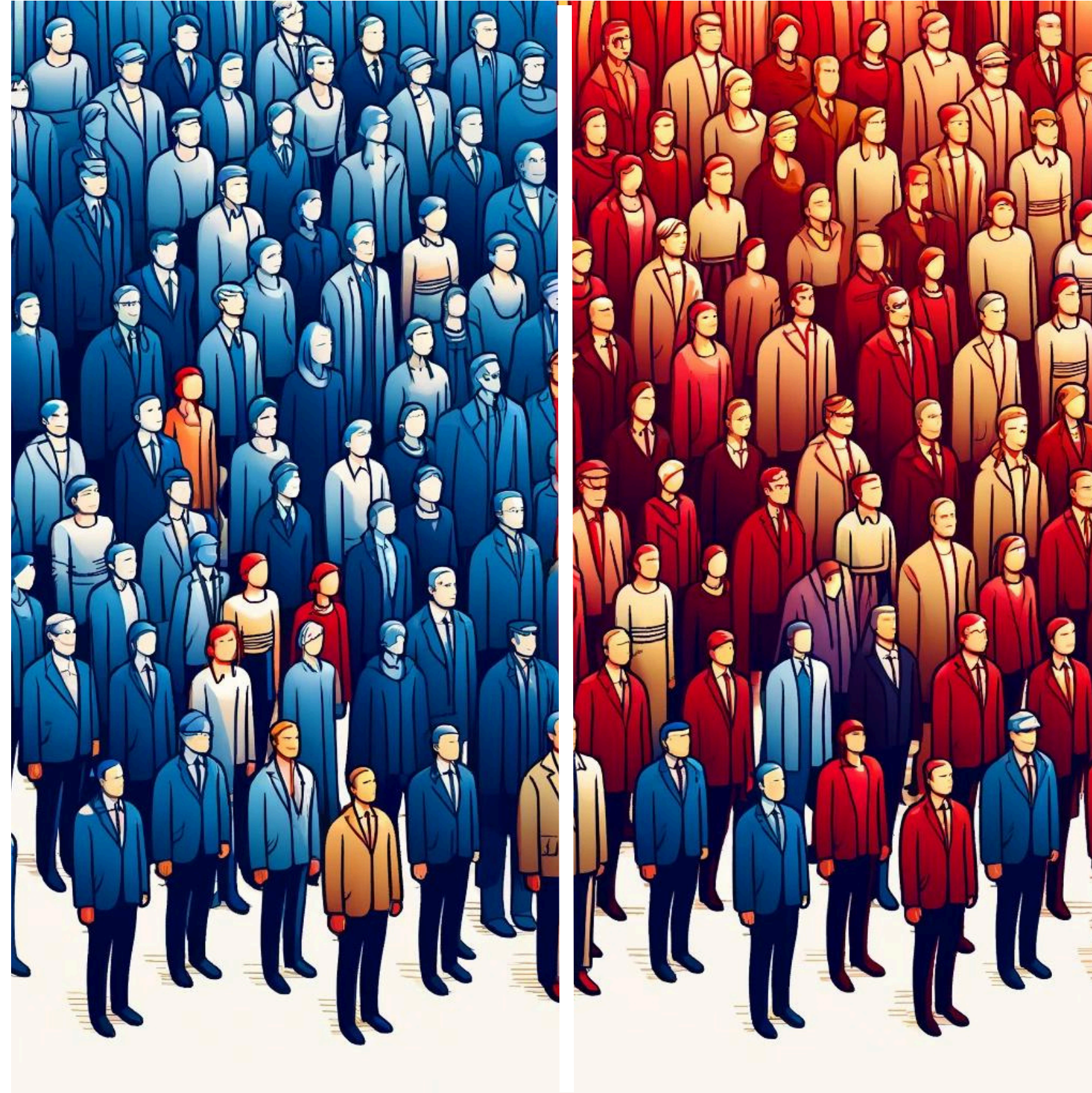


**High-
performance
Customer**

Group 0

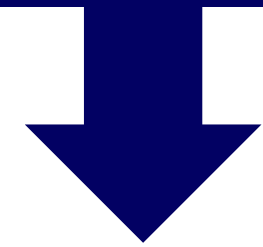


*Customer to be **accepted***



**Low-
performance
Customer**

Group 1



*Customer to be **reviewed***

3. Methodology

Methodology

Classification Model

XGBoost

Model Features

Gradient Boosting

Reduces bias and improves model accuracy

L1 (Lasso) and L2 (Ridge) Regularization Optimization

Controls complexity and improves the model's robustness against noise

Efficient Handling of Missing Data

Simplifies data processing when handling incomplete datasets

Feature Selection

Helps reduce overfitting

Handling Class Imbalance

Ensures accurate classification of minority classes

Methodology

Regularization Technique

Early Stopping

The model's training is monitored on a validation set, and stops once improvements stop, preventing overfitting

Advantages of Early Stopping

Prevents Overfitting

Reduces Training Time

Improves Model Performance

Optimizes Computational Resources

Facilitates Model Interpretation and Fine-Tuning

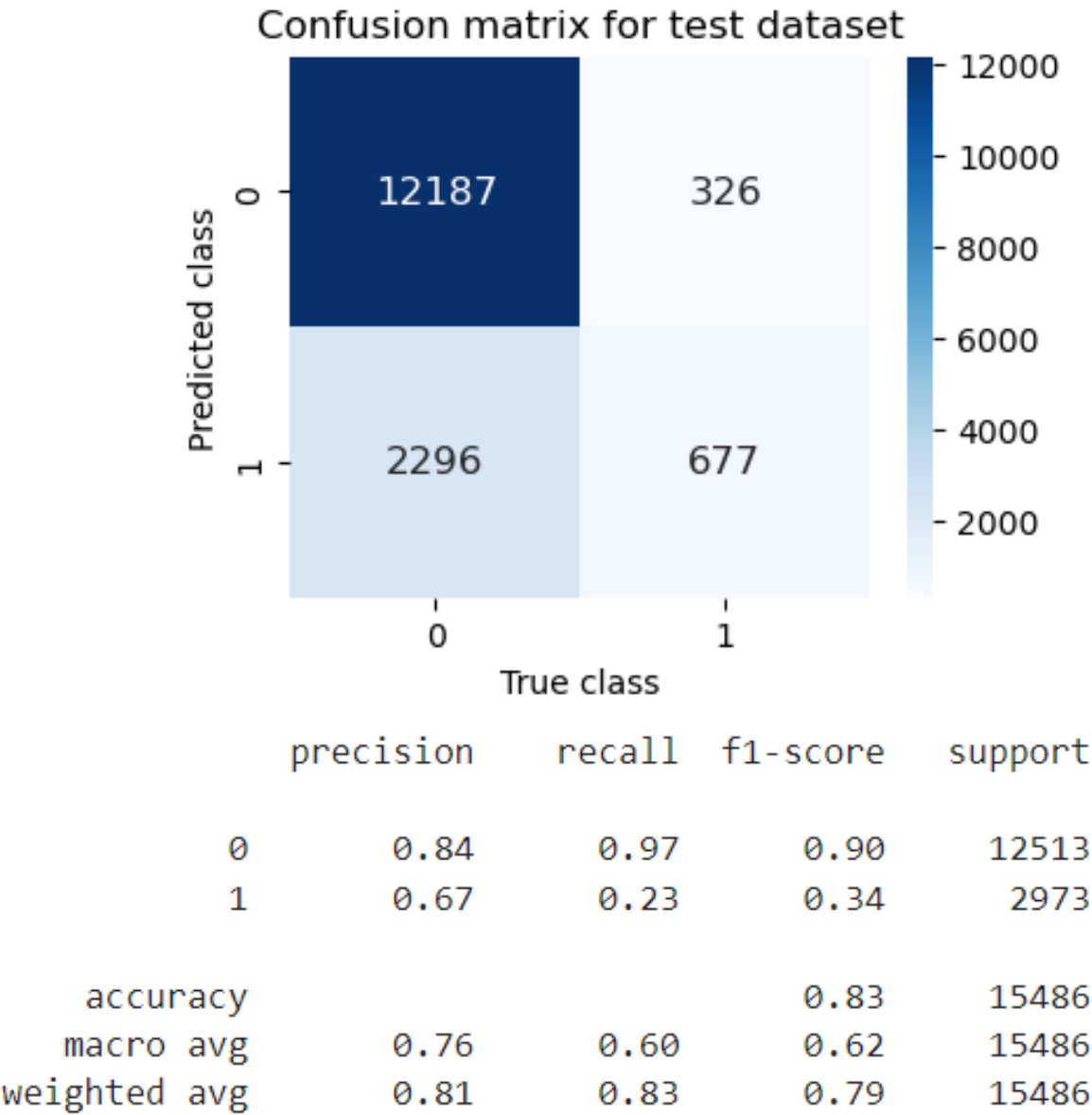
4. Results

Model Results

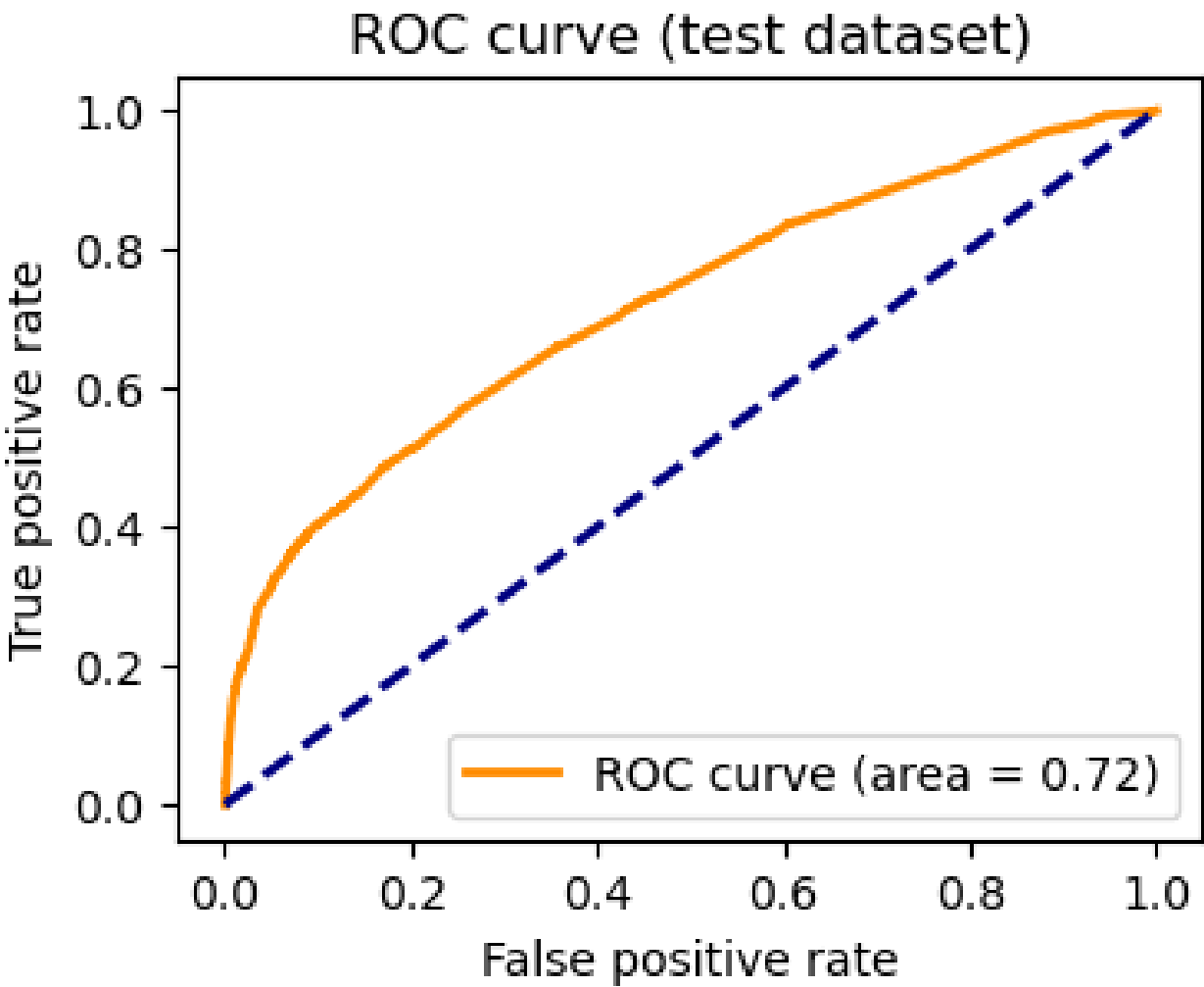


Total customers in test: **15,486**

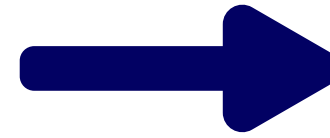
Confusion Matrix Classification Report



Area Under the Curve Score



Model Results

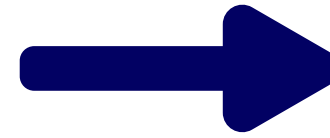


Total customers in test: **15,486**

Accuracy of the model is **0.83**

ROC AUC score is **0.72**

Model Results



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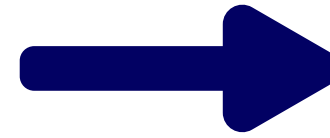
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94% of customers classified as
"High-performance"

6% of customers classified as
"Low-performance"

Model Results



Total customers in test: **15,486**

Accuracy of the model is **0.83**

ROC AUC score is **0.72**

94% of customers classified as
"High-performance"

6% of customers classified as
"Low-performance"

Before

Profit:
406,006 euros

After

Profit:
1,232,66 euros

5. Conclusions and Future Work

Conclusions

- The model accurately predicts and classifies new customers into high and low-performance groups.
- Supports decision-making by enabling customized policies and reducing financial risks.
- Tripled company benefits.
- True value in identifying low-performance customers, preventing financial losses and higher operational costs.

Conclusions

- The model accurately predicts and classifies new customers into high and low-performance groups.
- Supports decision-making by enabling customized policies and reducing financial risks.
- Tripled company benefits.
- True value in identifying low-performance customers, preventing financial losses and higher operational costs.

Future Work:

- *Extend model to other types of insurance policies beyond car insurance.*
- *Identify new variables to include in the model, aligning with the regulatory framework.*

Thank you for your attention!



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