

Research seminar I

Understanding Customer Behavior Through Data Analytics in the Banking Sector

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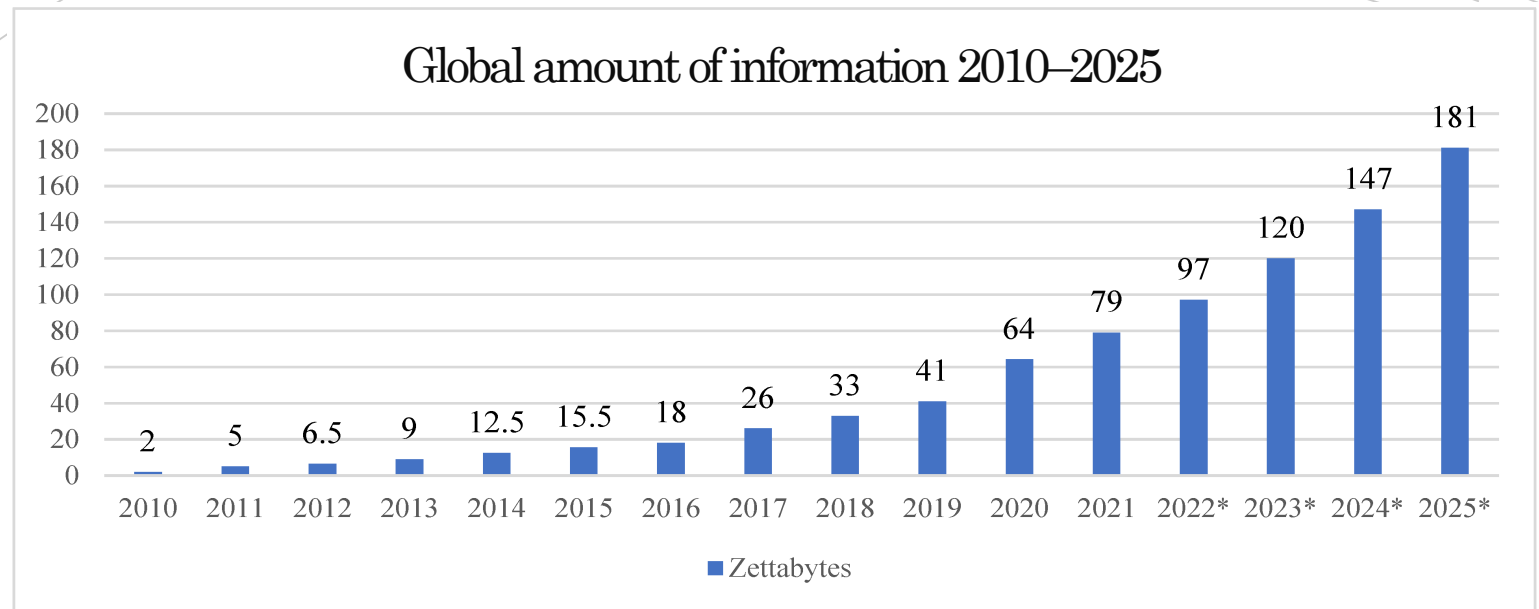
Introduction

- Irrelevant bank offers?
- A huge amount of customer data
 - Data \neq understanding
 - Analytics reveals patterns
- Smarter, personalized banking
 - Focus of this research

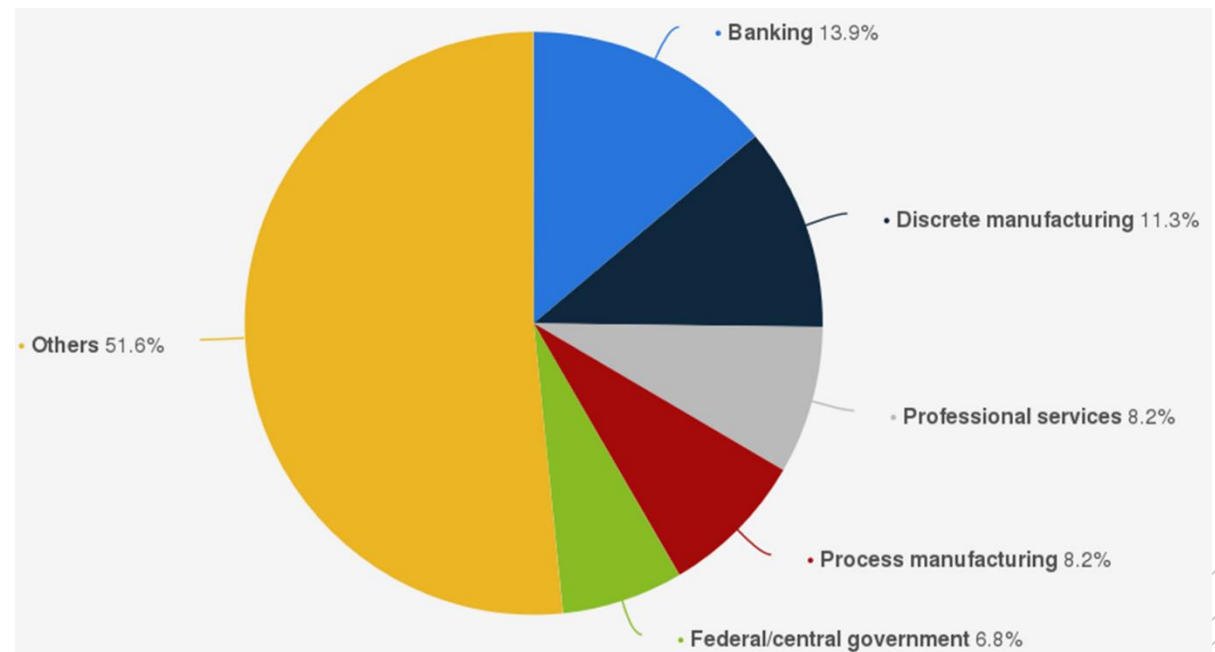
BIG data

GLOBAL amount of information

Share of big data and business analytics revenues worldwide in 2019, by industry



Adapted from Volume of data/information created, captured, copied, and consumed worldwide from 2010 to 2024, by A. Holst, 2021, Statista



Adapted from Worldwide big data and business analytics (BDA) revenue from 2015 to 2022, by segment, by Statista, 2021

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Research Aim and Problem Statement

- Banks misread customers
- Wasted offers & resources
- Need behavioral insight
- Goal: smarter decisions
- Focus: data + ML tools
- Key question: how to use data?

Theoretical Background

Data-Driven Decision-Making

- actual data—not assumptions

Behavioral Modeling

- machine learning to predict what customers are likely to do

Customer Relationship Management

- understanding and responding to customer needs

Literature Review Highlights

iCARE: data-based profiling

- big data to profile customers and guide marketing strategies

Personalized services

- big data enables banks to personalize service

Omni-channel behavior

- omni-channel banking
- informed customers make better decisions

DDDM boosts productivity

- data-driven decision-making
- productivity increases

Cultural barriers

- tech alone isn't enough
- leadership support
- data-ready culture

ML beats older methods

- neural networks and decision trees are outperforming older methods

Credit scoring

Churn prediction

Areas of
application

Fraud detection

Product
recommendations

Credit scoring

- Beyond credit history
- ML improves predictions
- Reaches “thin-file” clients
- Bias + fairness concerns
- Need transparent models

How to Quantify Credit Risk



Probability of default



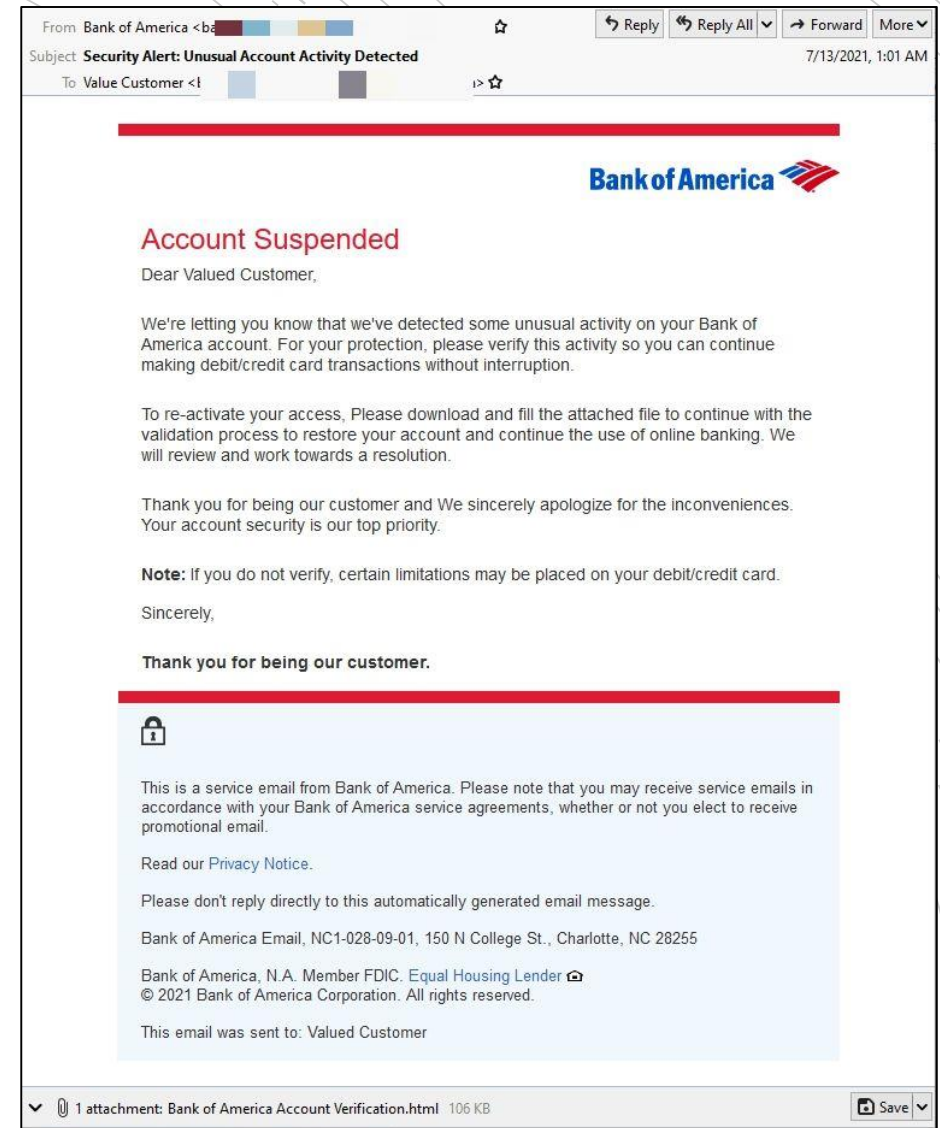
Loss given default



Exposure at default

Fraud Detection

- Complex, evolving threats
- Rule-based → ML models
- Real-time fraud detection
 - High accuracy (93%)
- Needs strong infrastructure



Churn prediction

- Spot at-risk customers
- ML models (e.g., XGBoost)
- Explainable AI (SHAP)
- Less product use = risk
- Boost retention efforts

Product Recommendations

- Personalized product offers
- No ratings? Use behavior
- Hybrid ML models work best
- Cold-start? Use demographics
- Improves targeting + trust

Discussion & Conclusion

- Proactive > reactive
- Personalized banking
- Fairness + transparency
- Culture + leadership matter
- Future: real-time, explainable AI
- Include smaller banks, all customers

THANK YOU FOR YOUR ATTENTION!

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