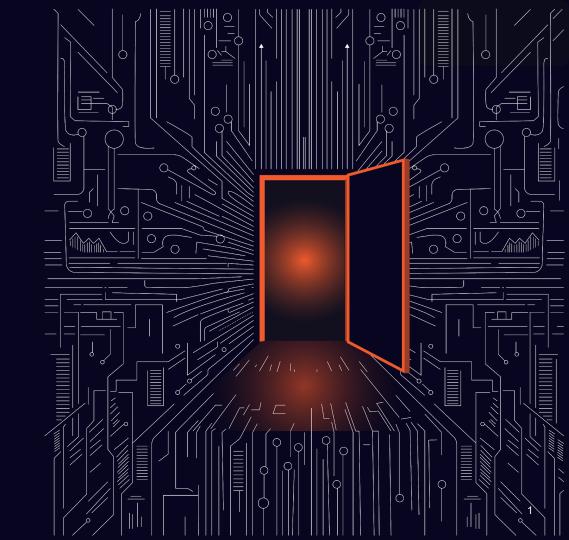
CARD CAI opportunity from complexity

Data Science





GAN-Driven Approaches to Transfer Learning in Tabular Data

Foundations and Potential Applications in Structured Finance



Agenda

1. Introduction

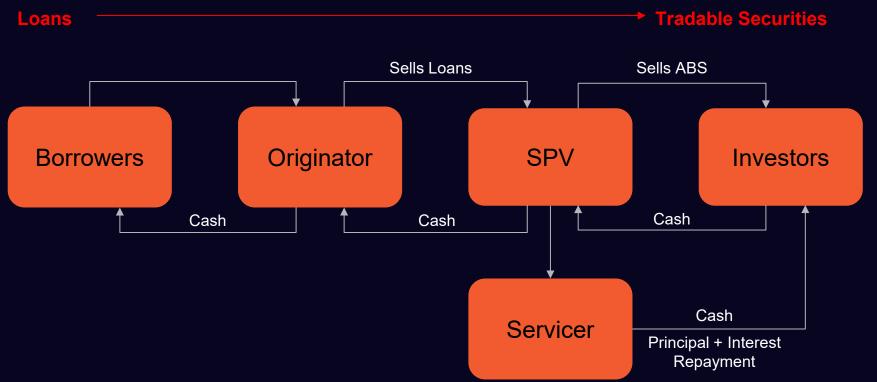
- a. What Cardo Al Does
- b. What is Securitisation?
- c. Sketching the problem

2. Generative Adversarial Networks for Tabular Synthetic Data Generation and Transfer Learning

- Generative Adversarial Networks (GANs)
 - i. Vanilla GANs
 - ii. f-Divergence Duality
 - iii. f-GANs
 - iv. Kantorovich-Rubinstein Duality and Wasserstein GANs
 - v. Conditional GANs
 - vi. Conditional Tabular GANs
 - vii. Transfer Learning in GANs

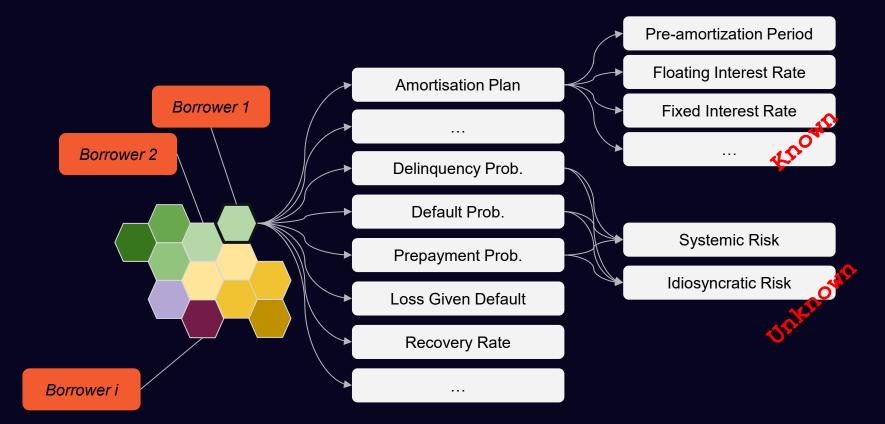


What is Securitisation?





Asset Pool Cash Flow



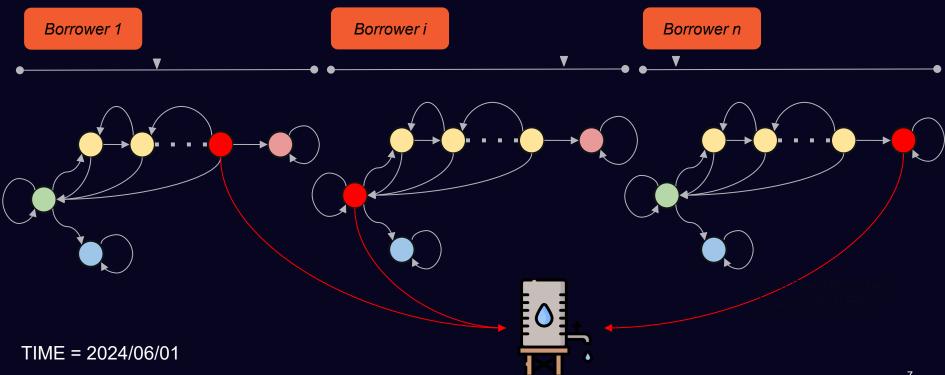


Asset Pool Cash Flow as a Markov Process

Installment i Issue Date **Maturity Date** Borrower 1 Delinquency Default Alive Prepayment

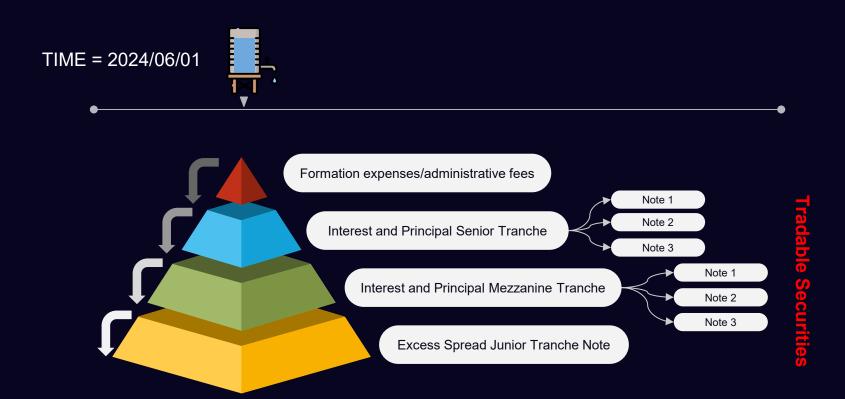


Asset Pool Cash Flow as a Markov Process



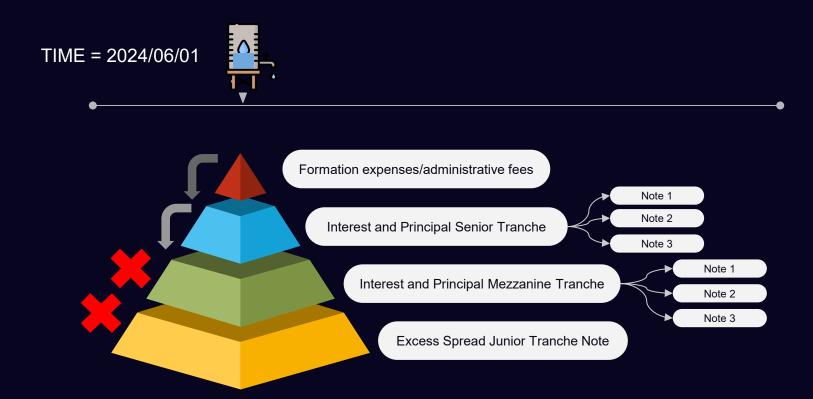


Cash Waterfall Structure





Cash Waterfall Structure





What are the Different Asset Classes in Securitisation?

- Mortgage-Backed Securities (MBS)
 - Residential Mortgage-Backed Securities (RMBS)
 - Commercial Mortgage-Backed Securities (CMBS)
- Asset-Backed Securities (ABS)
 - Auto Loans
 - Credit Card Receivables
 - Student Loans
 - Equipment Leases
 - Consumer Loans
 - Small Medium Enterprises Loans
- Collateralized Debt Obligations (CDOs)
 - Collateralized Loan Obligations (CLOs)
 - Collateralized Bond Obligations (CBOs)
- Whole Business Securitization
 - Revenue from entire businesses or franchises
- Future Flow Securitization
 - Securities backed by expected future receivables



In the context of loan default classification, we aim to leverage synthetic data generation for tabular transfer learning.

This approach aims to overcome several challenges. **Unbalanced datasets** are a significant issue, as default cases often constitute a minority, making model training difficult. Moreover, banks do not share **proprietary datasets**, seeking predictions without exposing sensitive loan information. **Privacy** is another key concern—borrower data must remain confidential and not directly used, adhering to privacy regulations. The **lack of historical data for new asset classes** further complicates model training. Additionally, **datasets can be noisy**, with past data containing inconsistencies and errors that affect model accuracy.

By implementing tabular synthetic data generation and transfer learning techniques, we seek to generate new balance datasets, protect privacy, address proprietary concerns, supplement data for new asset classes, and mitigate noise.



DATA SOURCE

Public Data Sources for Multiple **Asset Classes** Classification DATA SOURCE DATA SOURCE DATA SOURCE **General Synthetic SME** CL **RMBS Data Model** Regression Private Data Sources Single **Asset Class** Clustering

Transfer Learning



Public Data Sources for Multiple **Asset Classes** Classification DATA SOURCE DATA SOURCE DATA SOURCE **General Synthetic SME** CL **RMBS Data Model** Regression Private Data Sources Single **Asset Class** Clustering **Transfer Learning** DATA SOURCE

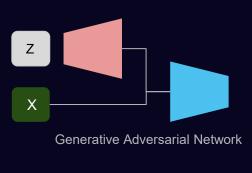


DATA SOURCE

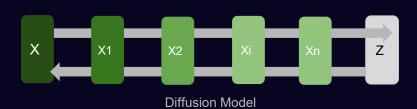
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Deep Generative Models for Synthetic Data Generation





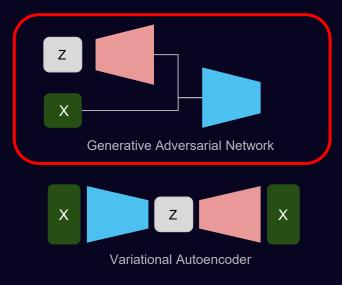


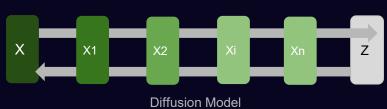
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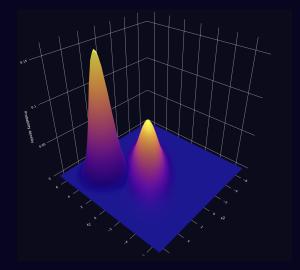
Generative models operate by analyzing patterns and distributions within their training data to generate new data from user inputs. Through training, the model learns to identify the joint probability distributions of features in the dataset. It then uses this knowledge to produce new data samples that closely resemble the original training data.



Deep Generative Models for Synthetic Data Generation



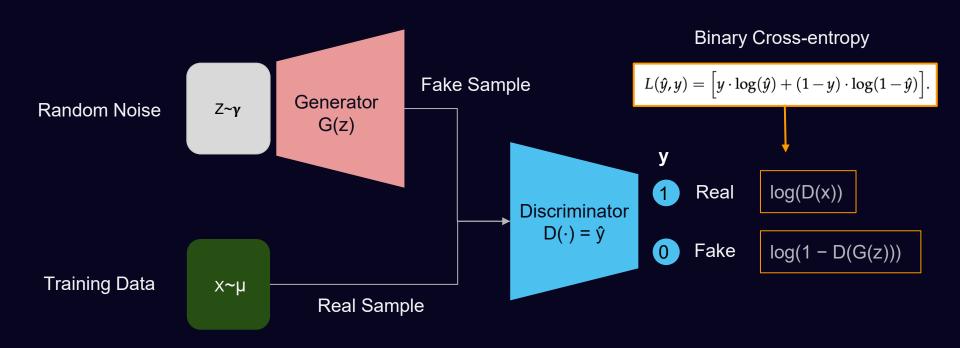




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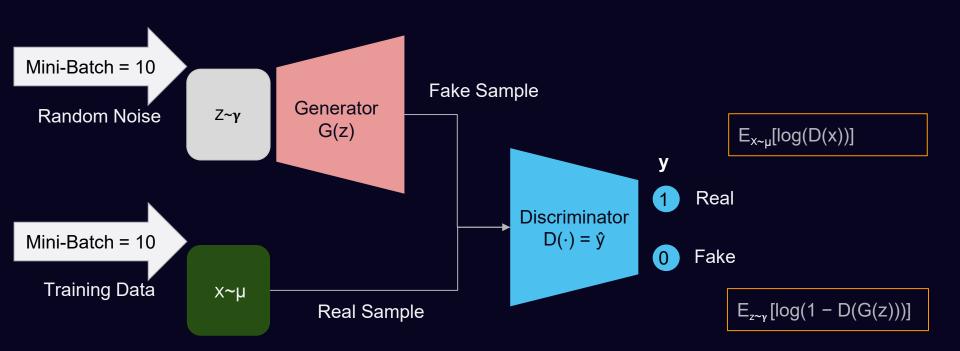


Generative Adversarial Network



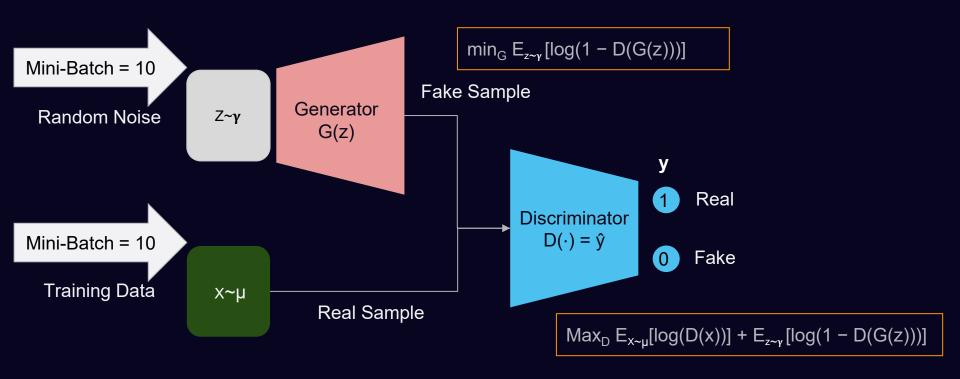


Generative Adversarial Network





Generative Adversarial Network





Generative Adversarial Networks for Tabular Synthetic Data Generation and Transfer Learning

- https://stefanopenazzi2.github.io/2025/01/05/F-Divergence-Duality.html
- https://stefanopenazzi2.github.io/2025/01/05/F-GANs.html
- https://stefanopenazzi2.github.io/2025/01/05/Kantorovich-Rubinstein-Duality.html
- https://stefanopenazzi2.github.io/2025/01/21/C-GANs.html
- https://stefanopenazzi2.github.io/2025/01/21/CT-GANs.html
- https://stefanopenazzi2.github.io/2025/01/22/TransferLearning-GANs.html



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