Deep Generative Models for Private Credit SPV Analytics

Cashflow Estimation and Portfolio Loss Distribution

Digital Finance Research

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Outline

Private Credit SPV Challenge

Special Purpose Vehicles (SPVs) in Private Credit

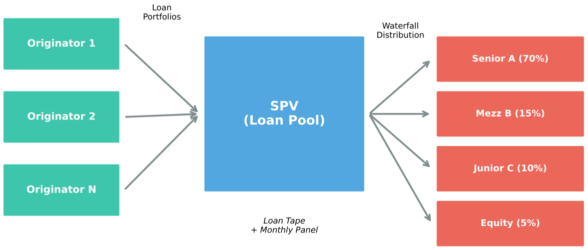
- Securitize portfolios of corporate, consumer, real estate, and trade receivables
- Need to estimate: loan-level cashflows, portfolio losses, tranche returns
- Required for: pricing, risk management, regulatory compliance (IFRS 9, Basel)

Key Modeling Challenges

- Heterogeneous loan characteristics across asset classes
- Macro-economic dependencies in default and prepayment
- Correlation structure for portfolio-level risk

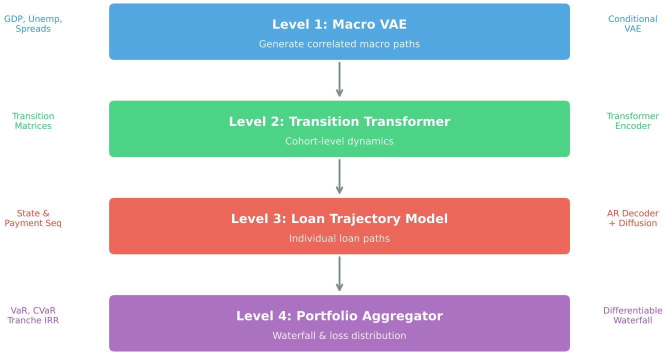
Traditional Markov models lack flexibility for complex dynamics

SPV Data Structure



Originators contribute loan portfolios; SPV tranches absorb losses in priority order

Hierarchical Deep Generative Framework



Four-level hierarchy: Macro $\rightarrow$ Cohort $\rightarrow$ Loan $\rightarrow$ Portfolio

Level 1: Macro Scenario Generator (VAE)

Conditional Variational Autoencoder for Macro Paths

- Generate correlated macro time series: GDP, unemployment, credit spreads
- Condition on scenario type: baseline, adverse, severely adverse
- Encoder-decoder with LSTM for temporal dynamics

Architecture

$$z \sim q_\phi(z|x, s), \quad \hat{x} = p_\theta(x|z, s)$$

where s is scenario label, z is latent code, x is macro path.

Enables joint generation and scenario-conditional stress testing

Level 2: Transition Transformer

Cohort-Level Transition Matrix Prediction

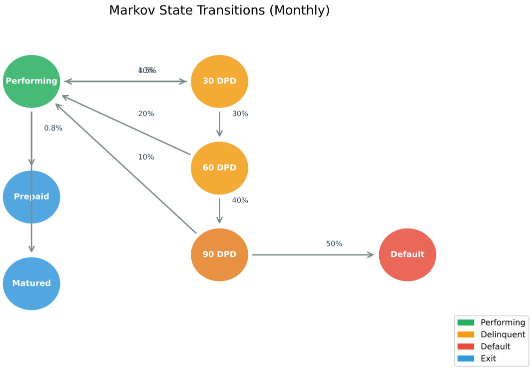
- Transformer encoder processes macro path + cohort features
- Outputs time-varying transition matrices P_t per cohort
- Captures systematic risk and macro sensitivity

Transition Probabilities

$$P_t(\text{state}_{t+1}|\text{state}_t, \text{macro}_t, \text{cohort}) = f_\theta(\text{macro}_{1:t}, \text{cohort})$$

Roll rates, cure rates, prepayment rates vary with economic conditions

Loan State Transitions



Seven-state Markov chain with absorbing states for default, prepayment, maturity

Level 3: Loan Trajectory Model

Autoregressive Generation of Individual Loan Paths

- Transformer decoder for state sequence (discrete)
- Diffusion head for payment amounts (continuous)
- Hazard rate module for default timing (survival)

Components

$$p(\text{state}_t, \text{payment}_t | \text{history}, \text{loan features}, \text{macro})$$

Captures heterogeneity within cohorts and idiosyncratic risk

Level 4: Portfolio Aggregator

Differentiable Waterfall for End-to-End Training

- Aggregate loan trajectories to portfolio cashflows
- Apply waterfall: fees $\rightarrow$ senior interest $\rightarrow$ mezzanine $\rightarrow$ equity
- Compute tranche-level metrics: IRR, loss rates, coverage ratios

Loss Distribution

$$\mathrm{VaR}_\alpha = F_L^{-1}(\alpha), \quad \mathrm{CVaR}_\alpha = \mathbb{E}[L | L > \mathrm{VaR}_\alpha]$$

Full distribution enables regulatory capital and pricing calculations

Loan Tape Structure

Static Features (At Origination)

Category	Features	Examples
Loan Terms	Balance, rate, term, amortization	EUR 500k, 6%, 60mo
Underwriting	LTV, DSCR, credit scores	75%, 1.3x, 720
Borrower	Industry, geography, type	Manufacturing, DE, SME
Collateral	Type, value, lien position	Real estate, EUR 650k

Time-Varying Features (Monthly Panel)

Category	Features
Balance	Current balance, scheduled/actual payment
Delinquency	Days past due, bucket (30/60/90+), cure flag
State	Performing, delinquent, default, prepaid, matured

Asset Class Specifications

Parameter	Corporate	Consumer	Real Estate	Receivables
Balance Range	100k–5M	1k–100k	50k–10M	1k–5M
Interest Rate	4–12%	5–20%	2–8%	3–10%
Term (months)	12–84	6–84	60–360	1–6
Annual Default	1–5%	2–8%	0.5–3%	0.5–2%
LGD	30–60%	60–90%	15–40%	20–50%

Different risk profiles require asset-class-specific calibration

Training Strategy

Stage 1: Pre-train Components Separately

- Macro VAE on historical macro series
- Transition Transformer on cohort-level roll data
- Loan trajectory model on loan-month panel

Stage 2: End-to-End Fine-Tuning

- Joint training with portfolio loss targets
- Adversarial scenarios for tail calibration

Stage 3: Calibration

- Match historical default rates and loss distribution moments
- Validate on out-of-sample vintages

Outputs and Use Cases

Output	Format	Use Case
PD Term Structure	Loan $\times$ Month matrix	Pricing, ECL calculation
LGD Distribution	Per-loan percentiles	Capital modeling
Cashflow Paths	$N_{\text{sim}} \times T$ matrix	DCF valuation
Loss Distribution	VaR, CVaR percentiles	Risk limits, capital
Tranche Returns	By tranche, by scenario	Investment decisions

Scenario Capabilities

- Baseline: unconditional generation from VAE
- Deterministic stress: fix macro path, generate loans
- Probabilistic stress: condition on tail of macro distribution
- Reverse stress: find macro path producing target loss

Summary

Contribution

- Hierarchical deep generative framework for private credit SPV analytics
- Macro VAE + Transition Transformer + Loan Trajectory + Portfolio Aggregator
- End-to-end differentiable for joint training and calibration

Advantages over Traditional Models

- Flexible: captures complex macro-credit dependencies
- Generative: full distribution, not just point estimates
- Scalable: handles large portfolios with heterogeneous assets
- Interpretable: hierarchical structure maps to business logic

Next Steps

- Calibration to historical CLO/ABS data
- Stress testing framework integration
- Real-time inference for portfolio monitoring

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