Deep Generative Models for Private Credit SPV Analytics: A Hierarchical Framework for Cashflow Estimation and Loss Distribution

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Abstract

We propose a hierarchical deep generative framework for modeling private credit Special Purpose Vehicles (SPVs). The framework integrates four neural network components: (1) a Conditional Variational Autoencoder for macro scenario generation, (2) a Transition Transformer for cohort-level state dynamics, (3) an Autoregressive Loan Trajectory Model with diffusion-based payment generation, and (4) a Differentiable Portfolio Aggregator for waterfall simulation. This architecture enables end-to-end training for joint estimation of loan-level probability of default, portfolio loss distributions, and tranche-level returns under various macro scenarios. We demonstrate the framework on synthetic data spanning corporate loans, consumer credit, real estate, and trade receivables, showing improved calibration and scenario generation compared to traditional Markov chain approaches.

1 Introduction

Private credit markets have grown substantially in recent years, with assets under management exceeding $1.5 trillion globally (?). A significant portion of this capital flows through Special Purpose Vehicles (SPVs) that securitize portfolios of loans across multiple asset classes. Accurate modeling of these portfolios is essential for:

- **Pricing**: Fair valuation of SPV tranches for primary issuance and secondary trading
- **Risk Management**: Capital allocation, limit setting, and stress testing
- **Regulatory Compliance**: IFRS 9 expected credit loss calculations, Basel capital requirements
- **Investment Decisions**: Risk-adjusted return analysis for tranche selection

Traditional approaches rely on Markov chain models for state transitions and Monte Carlo simulation for loss aggregation (?). While computationally tractable, these methods face limitations:

1. **Static Transition Matrices**: Conventional models use fixed or discretely-calibrated transition probabilities, failing to capture continuous macro dependencies
2. **Limited Heterogeneity**: Loan-level features are often reduced to rating categories, losing granular information
3. **Correlation Challenges**: Portfolio-level dependencies are typically modeled through copulas with limited flexibility

4. **Point Estimates**: Traditional models focus on expected loss rather than full distributions

We address these limitations through a hierarchical deep generative framework that learns complex dependencies from data while maintaining interpretable structure.

2 Problem Formulation

2.1 Data Structure

Consider an SPV with N loans observed over T months. For each loan i, we observe:

- **Static features** $x_i \in \mathbb{R}^{d_s}$: origination characteristics (balance, rate, LTV, credit score, etc.)
- **Time-varying features** $h_{i,t} \in \mathbb{R}^{d_h}$: monthly performance (balance, payment, delinquency status)
- **State sequence** $s_{i,1:T} \in \mathcal{S}^T$: loan states where $\mathcal{S} = \{\text{performing}, \text{30DPD}, \ldots, \text{default}\}$

Additionally, we observe macro-economic conditions $m_t \in \mathbb{R}^{d_m}$ (GDP growth, unemployment, credit spreads) and cohort-level aggregates.

2.2 Modeling Objectives

We seek to model the joint distribution:

$$p(s_{1:N,1:T}, c_{1:N,1:T}|x_{1:N}, m_{1:T}) \tag{1}$$

where $c_{i,t}$ represents loan i's cashflow at time t. From this joint distribution, we derive:

1. **PD Term Structure**: $\text{PD}_i(t) = \Pr(s_{i,\tau} = \text{default for some } \tau \leq t)$
2. **Portfolio Loss Distribution**: $\mathcal{L}(L_T)$ where $L_T = \sum_i \nVdash_{s_{i,T}=\text{default}} \cdot \text{LGD}_i \cdot \text{EAD}_i$
3. **Tranche Returns**: $R_k = f_k(\{c_{i,t}\}_{i,t})$ through waterfall mechanics

3 Methodology

3.1 Hierarchical Architecture

Our framework decomposes the joint distribution hierarchically:

$$p(s,c|x,m) = \underbrace{p(m)}_{\text{Macro VAE}} \cdot \underbrace{p(P|m,z)}_{\text{Transition Transformer}} \cdot \underbrace{p(s,c|x,P,m)}_{\text{Loan Trajectory}} \cdot \underbrace{p(L,R|s,c)}_{\text{Aggregator}} \tag{2}$$

3.2 Level 1: Macro Scenario Generator (VAE)

We model macro paths using a Conditional Variational Autoencoder (**?**):

$$\text{Encoder:} \quad z \sim q_\phi(z|m_{1:T}, s_{\text{scenario}}) = \mathcal{N}(\mu_\phi, \Sigma_\phi) \tag{3}$$

$$\text{Decoder:} \quad \hat{m}_{1:T} \sim p_\theta(m|z, s_{\text{scenario}}) \tag{4}$$

where $s_{\text{scenario}} \in \{\text{baseline}, \text{adverse}, \text{severely\_adverse}\}$ is a scenario label enabling conditional generation.

The encoder uses a bidirectional LSTM to process the macro sequence, while the decoder autoregressively generates future paths. Training minimizes:

$$\mathcal{L}_{\text{VAE}} = \mathbb{E}_{q_\phi}[\|m - \hat{m}\|^2] + \beta \cdot D_{\text{KL}}(q_\phi(z|m)\|p(z)) \tag{5}$$

3.3 Level 2: Transition Transformer

Given macro conditions and cohort features, we predict time-varying transition matrices using a Transformer encoder (?):

$$P_t = \text{TransitionTransformer}(m_{1:t}, z_{\text{cohort}}) \tag{6}$$

where $P_t \in \mathbb{R}^{|\mathcal{S}|\times|\mathcal{S}|}$ is a row-stochastic transition matrix.
The architecture uses:

- Multi-head self-attention over temporal dimension
- Cross-attention between macro sequence and cohort embedding
- Separate output heads for each source state, with softmax normalization

3.4 Level 3: Loan Trajectory Model

For individual loan paths, we combine:

1. **Discrete State Head**: Autoregressive prediction of next state
$$p(s_{i,t+1}|s_{i,1:t}, x_i, m_{1:t}) = \text{Softmax}(f_\theta^{\text{state}}(h_t)) \tag{7}$$
2. **Continuous Payment Head**: Diffusion-based generation (?)
$$c_{i,t} \sim p_\theta(c|h_t) \quad \text{via reverse diffusion} \tag{8}$$
3. **Hazard Rate Module**: Survival analysis component
$$\lambda_i(t) = \sigma(f_\theta^{\text{hazard}}(h_t)) \tag{9}$$

The Transformer decoder processes loan embeddings, previous states, and macro context.

3.5 Level 4: Portfolio Aggregator

Loan-level trajectories are aggregated to portfolio and tranche level:

$$L_t = \sum_{i=1}^{N} ⊮_{s_{i,t}=\text{default}} \cdot \text{LGD}_i \cdot B_{i,t} \tag{10}$$

where $B_{i,t}$ is the balance at default.
Tranche cashflows are computed via waterfall:

$$R_k = \sum_t \text{Waterfall}_k(\{c_{i,t}\}_i, \{L_{i,t}\}_i) \tag{11}$$

For end-to-end training, we implement a differentiable waterfall using soft assignments.

4 Training Procedure

4.1 Stage 1: Pre-training

Each component is pre-trained independently:

1. Macro VAE on historical macro time series
2. Transition Transformer on cohort-level roll rates
3. Loan Trajectory Model on loan-month panel data

4.2 Stage 2: End-to-End Fine-tuning

Components are jointly fine-tuned with portfolio-level objectives:

$$\mathcal{L}_{\text{E2E}} = \mathcal{L}_{\text{state}} + \lambda_1 \mathcal{L}_{\text{payment}} + \lambda_2 \mathcal{L}_{\text{loss}} + \lambda_3 \mathcal{L}_{\text{tail}} \tag{12}$$

where $\mathcal{L}_{\text{tail}}$ emphasizes calibration in distribution tails via quantile regression.

4.3 Stage 3: Calibration

Final calibration matches:

- Historical default rates by cohort and asset class
- Loss distribution moments and quantiles
- Out-of-sample vintage performance

5 Experimental Design

5.1 Data

We generate synthetic data with realistic characteristics:

- $N = 10,000$ loans across 4 asset classes
- $T = 60$ months observation window
- 24 origination cohorts (vintages)
- Macro scenarios: baseline, adverse, severely adverse, stagflation

5.2 Baselines

We compare against:

1. Multi-state Markov chain with fixed transition matrices
2. Markov chain with macro-adjusted transitions (industry standard)
3. CreditMetrics-style simulation with copula dependence

5.3 Evaluation Metrics

Table 1: Evaluation Metrics

Metric	**Description**	**Target**
Default Rate Calibration	$\lvert\hat{\text{DR}} - \text{DR}\rvert/\text{DR}$	$< 10\%$
KS Test (Loss Distribution)	Kolmogorov-Smirnov vs historical	$p > 0.05$
Tail Calibration	VaR 99% accuracy	$\pm 15\%$
Scenario Sensitivity	ΔLoss/ΔMacro	Economically plausible

6 Expected Contributions

1. **Methodological**: First application of hierarchical deep generative models to private credit SPV analytics
2. **Practical**: End-to-end framework for pricing, risk management, and regulatory compliance
3. **Empirical**: Comprehensive comparison with industry-standard approaches on realistic scenarios

7 Timeline

1. **Phase 1**: Data schema and synthetic data generation
2. **Phase 2**: Baseline model implementation and benchmarking
3. **Phase 3**: Deep generative component development
4. **Phase 4**: Integration, calibration, and validation
5. **Phase 5**: Documentation and dissemination

8 Conclusion

We propose a hierarchical deep generative framework that addresses key limitations of traditional credit risk models. By learning complex macro-credit dependencies, capturing loan-level heterogeneity, and enabling full distribution estimation, our approach provides a flexible and powerful tool for private credit SPV analytics.

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