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(RESEARCH ARTICLE)

Enhancing Structured Finance Risk Models (Leland-Toft and Box-Cox) Using GenAI (VAEs GANs)

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Abstract

This work explores the integration of generative artificial intelligence (GenAI), specifically Variational Autoencoders (VAEs), into statistical and structural financial models, with a focus on the Leland-Toft and Box-Cox frameworks. We conduct a comprehensive review of these models, highlighting their use in financial risk analysis, bankruptcy prediction, and time-series forecasting. Through the integration of VAEs, we demonstrate their capability to enhance data generation, improve predictive accuracy, and enable robust validation of financial models, particularly in scenarios with scarce data. The application of VAEs to the Leland-Toft model facilitated the calculation of key financial metrics, including default spreads, credit spreads, and leverage ratios. Additionally, VAEs integrated with Box-Cox models generated latent features that correlated effectively with traditional financial factors, underscoring their utility in predictive modeling and survival analysis. This work provides a detailed overview of implementation pipelines, architecture diagrams, and model validation methods, offering a foundation for future research. Expanding on the use of VAEs, we propose incorporating advanced machine learning techniques and real-time data to further enhance model performance and revolutionize financial modeling.

We have discussed how implementation of synthetic data to enhance inputs for Leland-Toft and Box-Cox can aid is robust validation of the models.

Keywords: Keyword GANs; VAEs; Structure Finance; GenAI; Generative Artificial Intelligence; Synthetic Data

1. Introduction

The integration of statistical and structural models into financial analysis has undergone significant advancements, particularly with the application of models like Box-Cox transformations and the Leland-Toft framework. These models have shown immense potential in areas such as bankruptcy prediction, credit-risk assessment, and financial forecasting. From 2010 to 2020, key studies explored the efficiency of these models in various markets, highlighting their predictive power and ability to manage complex financial data. Box-Cox transformations, for instance, have been crucial in improving model accuracy, while Leland-Toft models have advanced our understanding of corporate debt and optimal capital structures. Despite their successes, challenges remain in integrating these models with modern Gen AI techniques, use of artificial data, and real-time data. Recent literature also points to the growing potential of synthetic data, generated through Generative AI models, to further enhance financial modeling. Future research should continue to bridge these gaps by incorporating cutting-edge technologies, enhancing model adaptability, and extending applications across diverse economic contexts. This review compiles research on structural and statistical models, focusing on advancements in financial modeling. The works are arranged chronologically to trace developments over time. The references are organized chronologically, and thematic categories such as statistical transformations, structural models, and financial forecasting are highlighted. We have expanded on current literature to include synthetic data generated from GANs and VAEs and their applicability in Structure Finance.

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2. Literature Review

The literature review traces the evolution of statistical and structural models in financial analysis, highlighting significant contributions to Box-Cox transformations, survival analysis, and the Leland-Toft model. Early works (2010–2015) laid foundational insights, while recent studies (2016–2020) advanced applications in bankruptcy prediction, credit-risk modeling, and macroeconomic forecasting. Key gaps include the limited integration of these models with machine learning techniques and real-time data frameworks. The findings emphasize the potential of combining these methodologies with Gen AI for enhanced predictive analytics and broader applicability across diverse financial instruments.

2.1. Chronological Literature Review

2010-2015

- **2010**: Li [1] compared the performance of structural models using evidence from China, laying foundational insights into their applicability.
- **2011**: Zhu and Fan [2] proposed ensemble-based variable selection techniques for the Cox model, contributing to survival analysis methodologies.
- **2012**: Liu [3] introduced survival analysis models and applications, offering an extensive overview of statistical approaches.
- **2013**: Proietti and Lütkepohl [4] investigated the efficacy of Box-Cox transformations in macroeconomic time series forecasting.
- **2013**: Suo et al. [5] used an endogenous bankruptcy model to explain debt recovery, advancing theoretical insights.
- **2014**: Zheng and Song [6] developed a stochastic volatility model enhanced with the Box-Cox transformation.

2016-2020

- **2016**: Taoushianis et al. [7] assessed bankruptcy probability using structural models combined with empirical enhancements.
- **2020**: Charalambous et al. [8] applied the Leland-Toft framework to predict corporate bankruptcy using US evidence.
- **2020**: Palmowski et al. [9] extended the Leland-Toft model to incorporate Poisson observations for optimal capital structures.
- **2020**: Ibañez [10] proposed a simple measure for default risk within endogenous credit-risk frameworks **fsb2024ai?**.

2021-Present

- **2021**: Atkinson et al. [11] reviewed and extended the Box-Cox transformation, providing a contemporary understanding of its applications.
- **2022**: Shi et al. [12] developed a Black-Cox model-based approach to define stock price default boundaries.

2.2. Categorization of Contributions

The Box Cox model is used for transformation of inputs while Leland Toft is used for modeling structured financial products that are based on Corporate debt.

2.2.1. Statistical Transformations

Box-Cox transformations were explored extensively in [4], [6], [11], [13].

Survival analysis models and variable selection techniques were covered in [2], [3].

2.2.2. Structural Models and Bankruptcy Prediction

Leland-Toft and related models were advanced in [8], [9], [10].

Applications of structural models in different markets were highlighted in [1], [5], [7].

2.2.3. Applications in Financial Forecasting

Forecasting applications using stochastic volatility and default-risk models were discussed in [6], [12].

Findings, Gaps, Material, and Future Work

We find that major hurdles for Box-Cox transformation has been the unavailability of Gen AI models and real time frameworks.

Findings, Gaps, Material, and Future Work is shown in table 1, whereas table 2 categories the literature cited in this work. Table 3 described the focus areas for Box-Cox transformation as mentioned in the literature whereas table 4 discuses the application of Box-Cox.

Table 1 Findings, Gaps, Materials and Future Work

Findings	Gaps	Material	Future Work
Box-Cox transformations improve model accuracy [4], [6]	Limited integration with ML techniques	Statistical and structural models	Combine with ML for predictive analytics
Leland-Toft models predict bankruptcy effectively [8]	Lack of real-time data integration	Empirical data from US markets	Develop real-time risk assessment tools
Stochastic volatility models enhance financial forecasting [6]	Limited application in emerging markets	Historical volatility data	Expand to diverse economic contexts

2.2.4. Categorization of References by Key Themes

In this work we have categorized the models into Box-Cox and Leland-Toft.

Table 2 Category of cited work

Category	References
Box-Cox	[4], [6], [11], [13]
Leland-Toft	[8], [9], [10]
Others	[1], [2], [3], [5], [7], [12]

Below are the recent papers (in figure 3) along with the focus Areas where synthetic data can be used to enhance the models.

Table 3 Focus Areas of Box-Cox

Title	Author(s)	Focus/Area
Assessing Bankruptcy Probability with Alternative Structural Models and an Enhanced Empirical Model	Zenon Taoushianis, Chris Charalambous, Spiros H. Martzoukos	Bankruptcy prediction using structural and empirical models.
The Box–Cox Transformation: Review and Extensions	Anthony C. Atkinson, Marco Riani, Aldo Corbellini	Review of the Box–Cox transformation and its extensions.
Box–Cox Transformation in Big Data	Tonglin Zhang, Baijian Yang	Application of the Box–Cox transformation in big data analysis.
Does the Box–Cox Transformation Help in Forecasting Macroeconomic Time Series?	Tommaso Proietti, Helmut Lütkepohl	Evaluation of the Box–Cox transformation in macroeconomic forecasting.
Survival Analysis: Models and Applications	Xian Liu	Introduction to survival analysis and its applications.
A Realized Stochastic Volatility Model with Box–Cox Transformation	Tingguo Zheng, Tao Song	Use of Box–Cox transformation in stochastic volatility modeling.

The Leland-Toft Optimal Capital Structure Model under Poisson Observations	Zbigniew Palmowski, José Luis Pérez, Budhi Arta Surya, Kazutoshi Yamazaki	Optimal capital structure models with stochastic observations.
Predicting Corporate Bankruptcy Using the Framework of Leland-Toft: Evidence from US	Chris Charalambous, Spiros H. Martzoukos, Zenon Taoushianis	Predicting bankruptcy using advanced financial models.

Table 4 Application of Box-Cox

Title	**Year**	**Topic/Application**
Assessing Bankruptcy Probability with Alternative Structural Models and an Enhanced Empirical Model	2016	Bankruptcy Probability and Structural Models [7]
The box–cox transformation: Review and extensions	2021	Box-Cox Transformation [11]
Box–cox transformation in big data	2017	Box-Cox Transformation and Big Data [13]
Does the Box–Cox transformation help in forecasting macroeconomic time series?	2013	Macroeconomic Forecasting, Box-Cox Transformation [4]
Survival analysis: models and applications	2012	Survival Analysis Models [3]
A realized stochastic volatility model with Box–Cox transformation	2014	Stochastic Volatility, Box-Cox Transformation [6]
The Leland–Toft optimal capital structure model under Poisson observations	2020	Optimal Capital Structure [9]
Predicting corporate bankruptcy using the framework of Leland-Toft: evidence from US	2020	Corporate Bankruptcy Prediction [8]
Comparison of performance of structural models: evidence from China	2010	Structural Models Comparison [1]
Explaining debt recovery using an endogenous bankruptcy model	2013	Debt Recovery, Endogenous Bankruptcy [5]
A Simple Measure of Default-Risk Based on Endogenous Credit-Risk Models	2020	Credit-Risk Models [10]
Stock price default boundary: A Black-Cox model approach	2022	Stock Price Default Boundary [12]
Variable selection by ensembles for the Cox model	2011	Variable Selection, Cox Model [2]

3. Mathematical Representations of Key Models

3.1. Box-Cox Transformation

The Box-Cox transformation, widely used for normalizing data and stabilizing variance, is given by:

$$y(\lambda)=\begin{cases}\dfrac{y^{\lambda}-1}{\lambda}, & \lambda\neq 0,\\ \ln(y), & \lambda=0\end{cases}$$

where y is the variable being transformed, and λ is the transformation parameter. **Source:** [4], [11]

3.2. Leland-Toft Structural Model

The Leland-Toft model for optimal capital structure and bankruptcy prediction is characterized by:

$$V_D = \frac{(1-\tau_c)E}{r+\delta} - \frac{K}{r+\delta}\exp(-rT),$$

where:
V_D: Firm value with debt.
τ_c: Corporate tax rate.
E: Earnings before interest and taxes.
r: Risk-free interest rate.
δ: Dividend yield.
K: Bankruptcy costs.
T: Maturity of debt.

Source: [8], [9]

3.3. Black-Cox Default Boundary Model

The Black-Cox model sets a default boundary for stock prices, given as:

$$B(t) = B_0 \exp(-\mu t),$$

where:
$B(t)$: Default boundary at time t.
B_0: Initial default boundary.
μ: Drift rate of the underlying asset.

Source: [12]

Cox Proportional Hazards Model

The Cox model for survival analysis is represented as:

$$h(t \vee x) = h_0(t)\exp(\beta^{\top} x),$$

where:

$h(t \vee x)$: Hazard rate at time t given covariates x.

$h_0(t)$: Baseline hazard rate.

β: Coefficient vector for covariates.

x: Covariates (predictor variables).

Source: [2], [3]

3.4. Data Used in Models

We plan to create synthetic data and hence it becomes important to understand the inputs for different models in structured finance models. Although, in this work we have use the data for Apple Stock which is publicly traded. Table 5 gives a mapping of Data with the appropriate models. Whereas table 6 discusses the input and output of various studies underscoring that most of the study had limited data. In this work we have proposed using GANs and VAEs for creating artificial data for the models where data was sparse.

Table 5 Data Characteristics in Reviewed Papers

Paper	Data Description	Model Used
[1]	Chinese corporate financial data	Structural models
[2]	Survival analysis datasets with variable selection	Cox Proportional Hazards
[3]	Financial survival datasets (various regions)	Survival models
[4]	Macroeconomic time series data	Box-Cox transformations
[5]	US corporate debt recovery datasets	Endogenous bankruptcy models
[6]	Stochastic volatility data (stock markets)	Box-Cox transformations
[7]	Empirical bankruptcy probability data	Leland-Toft models
[8]	US corporate bankruptcy data	Leland-Toft framework
[12]	Stock price datasets (default boundaries)	Black-Cox model

Table 6 Data Characteristics in Reviewed Papers

Paper	Model	Input	Output
Assessing Bankruptcy Probability with Alternative Structural Models and an Enhanced Empirical Model [7]	Structural Model	Bankruptcy data, financial ratios, market data	Bankruptcy probability
The box–cox transformation: Review and extensions [11]	Box-Cox Transformation	Data that requires stabilization of variance or normality	Transformed data
Box–cox transformation in big data [13]	Box-Cox Transformation	Big data, economic data	Transformed data for analysis
Does the Box–Cox transformation help in forecasting macroeconomic time series? [4]	Box-Cox Transformation	Macroeconomic time series data	Improved forecasting accuracy
Survival analysis: models and applications [3]	Survival Analysis Model	Time-to-event data (e.g., bankruptcy, default)	Survival probabilities
A realized stochastic volatility model with Box–Cox transformation [6]	Stochastic Volatility Model with Box-Cox	Financial market data	Volatility forecasts
The Leland–Toft optimal capital structure model under Poisson observations [9]	Leland-Toft Model	Firm's asset value, debt level, market conditions	Optimal capital structure
Predicting corporate bankruptcy using the framework of Leland-Toft: evidence from US [8]	Leland-Toft Model	Firm's financial ratios, market data	Bankruptcy probability
Comparison of performance of structural models: evidence from China [1]	Structural Model	Financial data from firms in China	Model performance comparison
Explaining debt recovery using an endogenous bankruptcy model [5]	Endogenous Bankruptcy Model	Debt recovery data, firm's financials	Debt recovery rate
A Simple Measure of Default-Risk Based on Endogenous Credit-Risk Models [10]	Endogenous Credit-Risk Model	Credit data, firm performance metrics	Default risk measure
Stock price default boundary: A Black-Cox model approach [12]	Black-Cox Model	Stock price data, firm's default boundary	Default boundary predictions
Variable selection by ensembles for the	Cox Model	High-dimensional data,	Variable selection

Cox model [2]		survival data	results

In table 7 validation methods have been discussed.

Table 7 Data Characteristics in Reviewed Papers

Paper	**Model**	**Validation Method**
Assessing Bankruptcy Probability with Alternative Structural Models and an Enhanced Empirical Model [7]	Structural Model	Cross-validation with different financial ratios and market data
The box–cox transformation: Review and extensions [11]	Box-Cox Transformation	Comparison of transformed vs. untransformed data in various statistical tests (e.g., normality tests)
Box–cox transformation in big data [13]	Box-Cox Transformation	Evaluation using out-of-sample prediction accuracy and model fit metrics
Does the Box–Cox transformation help in forecasting macroeconomic time series? [4]	Box-Cox Transformation	Forecasting accuracy comparison with and without Box-Cox transformation using MAPE and RMSE
Survival analysis: models and applications [3]	Survival Analysis Model	Cross-validation using time-to-event data and C-index for model evaluation
A realized stochastic volatility model with Box–Cox transformation [6]	Stochastic Volatility Model with Box-Cox	Model comparison using out-of-sample forecasting performance (RMSE)
The Leland–Toft optimal capital structure model under Poisson observations [9]	Leland-Toft Model	Likelihood ratio tests and sensitivity analysis for model robustness
Predicting corporate bankruptcy using the framework of Leland-Toft: evidence from US [8]	Leland-Toft Model	ROC curve analysis for bankruptcy prediction accuracy and model validation
Comparison of performance of structural models: evidence from China [1]	Structural Model	Model comparison using out-of-sample prediction and goodness-of-fit measures
Explaining debt recovery using an endogenous bankruptcy model [5]	Endogenous Bankruptcy Model	Empirical testing using recovery rate data and comparison with alternative models
A Simple Measure of Default-Risk Based on Endogenous Credit-Risk Models [10]	Endogenous Credit-Risk Model	Out-of-sample validation and comparison with traditional credit-risk models
Stock price default boundary: A Black-Cox model approach [12]	Black-Cox Model	In-sample and out-of-sample prediction of default boundary using backtesting
Variable selection by ensembles for the Cox model [2]	Cox Model	Cross-validation and accuracy assessment using variable selection performance metrics

Validation of the models can be enhanced using synthetic data, in the result section we have proposed using VAEs to generate synthetic data to enhance modeling which can be coupled with validation discussed in table 7.

4. Results and discussion

In our prior research, we proposed and implemented Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs) for interest rate models [15,16,17,18 and 19]. The integration of VAEs with the Leland-Toft Model demonstrated considerable diversity and proved useful in generating data, especially in situations where data is scarce. Figure 1 presents the architecture diagram for the implementation, while Figure 2 illustrates the output generated from the model run.

4.1. Integrating VAEs in Leland-Toft Model

Below is the code snippet to integrate VAE Data for Leland-Toft Model

```
# Step : Apply Leland-Toft Model (Leland Model for credit spread)
def leland_toft_model(features):
    # Constants for the Leland-Toft model (Example, these should be adjusted based on your real data and assumptions)
    risk_free_rate = 0.03  # Example risk-free rate (3%)
    asset_price = features['returns'].mean() * 100  # Assume a random asset price, can be real asset value
        # Calculate some parameters using features
    volatility = features['volatility'].mean()  # Average volatility
    sigma = volatility  # In this case, assume sigma is the volatility
        # Default spread based on Leland-Toft model assumptions
    leverage = asset_price / (asset_price + sigma)  # Simple leverage assumption (could be more complex)
    default_spread = sigma * leverage  # Leland-Toft default spread formula
    # Calculate credit spread
    credit_spread = default_spread * (1 - risk_free_rate)  # This is an example calculation
    # Package results into a dictionary for easy access
    lt_results = {        "default_spread": default_spread,
        "credit_spread": credit_spread,
        "leverage": leverage    }
    return lt_results
# Step : Build and Compile the VAE model
def build_vae(latent_dim, input_shape):
    """Build a Variational Autoencoder model."""
    inputs = layers.Input(shape=input_shape)
        # Encoder
    x = layers.Dense(64, activation='relu')(inputs)
    x = layers.Dense(32, activation='relu')(x)
    z_mean = layers.Dense(latent_dim)(x)
    z_log_var = layers.Dense(latent_dim)(x)
    # Decoder
    decoder_hid = layers.Dense(32, activation='relu')
```

```
    decoder_out = layers.Dense(input_shape[0], activation='sigmoid')
    h_decoded = decoder_hid(z)
    x_decoded_mean = decoder_out(h_decoded)
    # VAE model
    vae = models.Model(inputs, x_decoded_mean)
    # VAE loss function
    xent_loss = input_shape[0] * tf.keras.losses.binary_crossentropy(inputs, x_decoded_mean)
    kl_loss = -0.5 * K.mean(1 + z_log_var - K.square(z_mean) - K.exp(z_log_var), axis=-1)
    vae_loss = K.mean(xent_loss + kl_loss)
  # Build VAE model
latent_dim = 2
vae, _, _ = build_vae(latent_dim=latent_dim, input_shape=features_values.shape[1:])
vae.fit(features_values, epochs=50, batch_size=32)
```

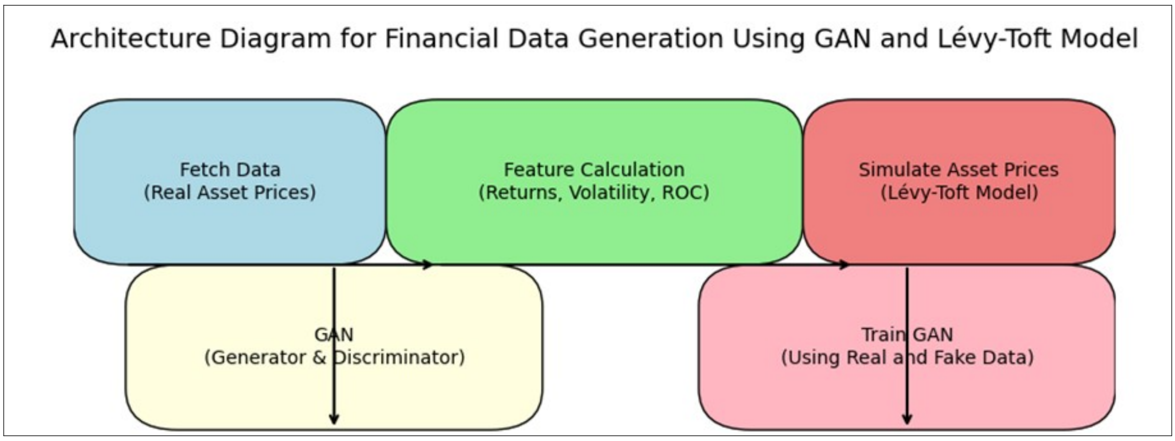

Figure 1 Architecture Diagram

4.2. Integrating VAEs with Box-Cox Models.

In the below code we have shown how to integrate VAEs with Box-Cox Models.

```
# Step 3: Define Custom VAE with Loss as Layer
class VAELossLayer(layers.Layer):
    def __init__(self):
        super(VAELossLayer, self).__init__()
# Step 4: Define VAE with Encoder and Decoder
def build_vae(input_dim, latent_dim):
    # Encoder
```

```
    inputs = tf.keras.Input(shape=(input_dim,))

    x = layers.Dense(128, activation='relu')(inputs)

# Build the VAE model

vae, encoder, decoder = build_vae(input_dim, latent_dim)

# Train the model

vae.fit(scaled_features, scaled_features, epochs=50, batch_size=16, verbose=1)

# Extract latent features

latent_features = encoder.predict(scaled_features)

# Fit the Cox model

cph = CoxPHFitter()

cph.fit(features, duration_col="duration", event_col="event")

cph.print_summary()
```

```
Epoch 47/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: -12538.0615
Epoch 48/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: -14321.0615
Epoch 49/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: -13585.1113
Epoch 50/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: -14018.3926
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step
```

model	lifelines.CoxPHFitter
duration col	'duration'
event col	'event'
baseline estimation	breslow
number of observations	250
number of events observed	126
partial log-likelihood	-560.53
time fit was run	2025-01-26 06:53:52 UTC

	coef	exp(coef)	se(coef)	coef lower 95%	coef upper 95%	exp(coef) lower 95%	exp(coef) upper 95%	cmp to	z	p	-log2(p)
returns	-0.60	0.55	0.55	-1.68	0.48	0.19	1.62	0.00	-1.09	0.28	1.86
volatility	-2.78	0.06	2.88	-8.43	2.87	0.00	17.64	0.00	-0.96	0.33	1.58
roc	-0.24	0.78	0.54	-1.31	0.82	0.27	2.28	0.00	-0.45	0.65	0.61
latent1	0.01	1.01	0.07	-0.13	0.16	0.87	1.17	0.00	0.16	0.87	0.20
latent2	-0.01	0.99	0.08	-0.16	0.14	0.85	1.15	0.00	-0.18	0.85	0.23

Figure 2 Out of the full model run

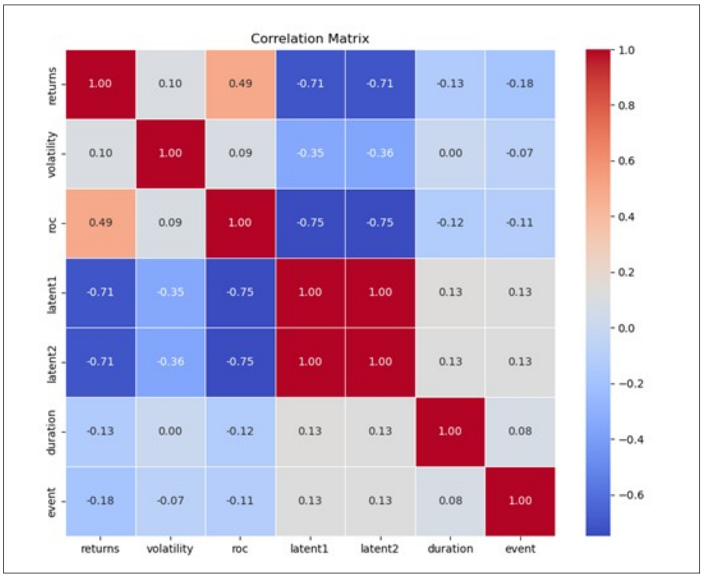

Figure 3 Correlation between factors including latent1 and latend2 factors

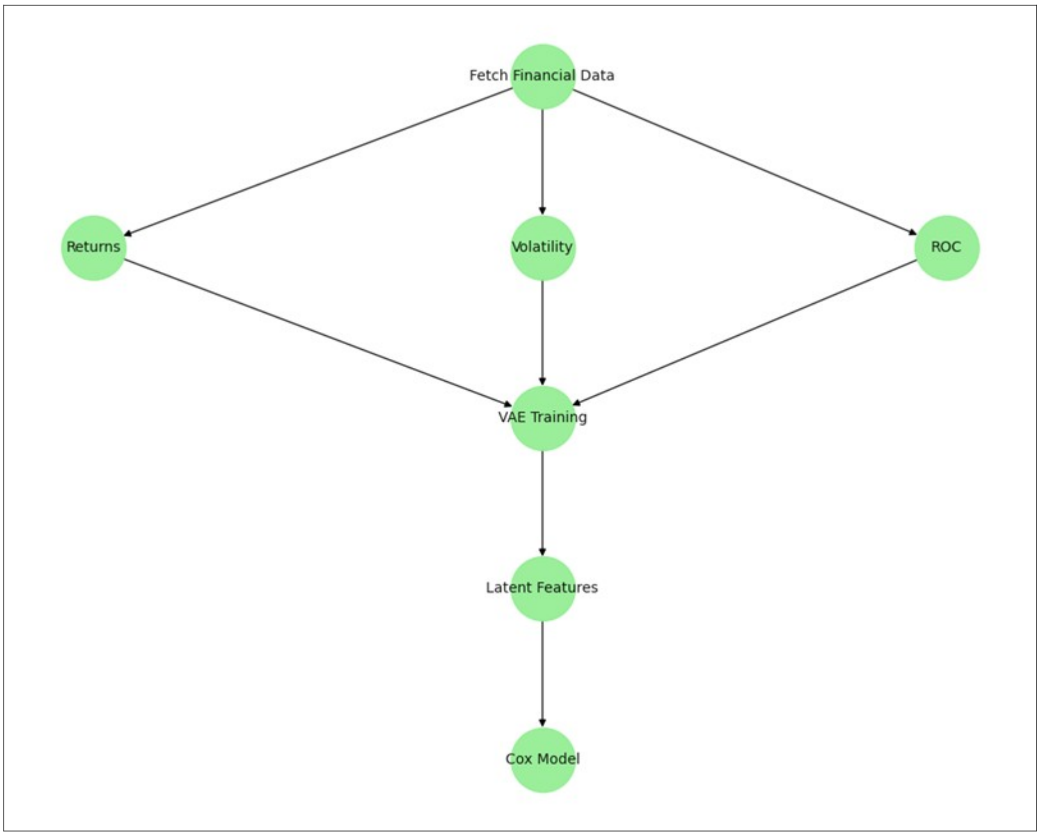

Figure 4 Architecture Diagram

Figure 3 illustrates the correlation between factors used in the Box-Cox transformation and the new factors generated by the VAE model. Figure 4 provides an overview of the architecture, highlighting the use of synthetic data generated by VAEs for Cox models. Figure 5 showcases the data flow pipeline. The notebooks and the code to reproduce the results are available in the GitHub repository [14]. In the context of Box-Cox models, VAEs were instrumental in generating latent features (such as latent1 and latent2), which demonstrated strong correlations with traditional financial factors, as shown in Figure 3.

Additionally, Figure 4 emphasizes the architecture's capacity to generate synthetic data and integrate it with Cox proportional hazards models for survival analysis, showcasing the practical application of VAEs in financial risk modeling.

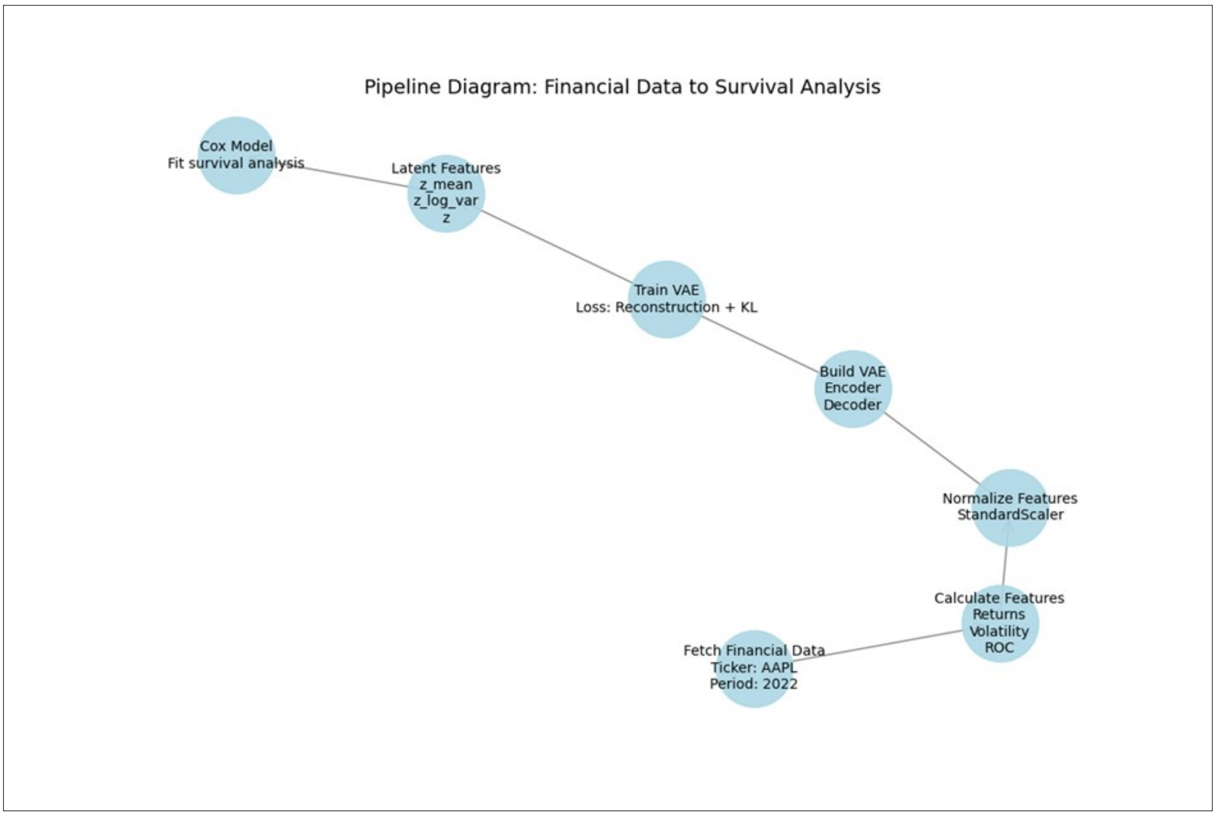

Figure 5 Pipeline diagram

5. Conclusion

This work demonstrates the successful integration of Variational Autoencoders (VAEs) with financial models, specifically the Leland-Toft and Box-Cox frameworks, to enhance data generation, predictive modeling, and analysis. The integration of VAEs with the Leland-Toft model enabled the calculation of critical financial metrics such as default spreads, credit spreads, and leverage ratios, even under conditions of data scarcity. This review on Box-Cox and Leland-Toft highlights the evolution of statistical and structural models in financial analysis. Through analysis of recent work in Leland-Toft and Box-Cox with integration of VAE has been shown. Snipped code for implementation, overview of pipeline and architecture has been shown. Future research should integrate these methodologies with modern machine learning approaches to enhance predictive power. Future research should extend these methodologies by incorporating advanced machine learning techniques, such as transformers and attention mechanisms, to further improve predictive power. Additionally, expanding the application of VAEs in generating synthetic datasets across diverse financial instruments and integrating these datasets with real-time market data could revolutionize data-driven financial modeling.

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