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Automated Adversarial Stress Testing Using Generative Adversarial Networks for Dynamic Risk Scenario Synthesis

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Abstract: Traditional stress testing frameworks rely heavily on manually designed macroeconomic scenarios that often fail to capture the nonlinear and adversarial characteristics of modern financial systems. This study proposes an automated adversarial stress testing framework based on Generative Adversarial Networks (GANs) to generate realistic yet extreme risk scenarios. The framework integrates scenario generation, adversarial perturbation, and risk propagation modeling to evaluate systemic resilience under previously unseen market conditions. The proposed approach allows financial institutions to move beyond static stress scenarios by synthesizing data-driven stress environments that reflect complex market dependencies. Experimental evaluation using historical financial indicators demonstrates that the GAN-based system produces high-impact stress trajectories capable of revealing latent vulnerabilities in risk portfolios. The results suggest that adversarial generative models can significantly enhance scenario diversity, improve tail-risk discovery, and support proactive regulatory stress testing.

Keywords: Adversarial Stress Testing; Generative Adversarial Networks; Financial Risk Modeling; Scenario Generation; Systemic Risk; Deep Learning

1. Introduction

Stress testing has become a central component of financial risk management since the global financial crisis. Regulatory frameworks such as those developed by the Basel Committee require financial institutions to evaluate resilience under severe but plausible scenarios. Despite their importance, existing stress testing methodologies suffer from several limitations.

First, most stress scenarios are manually designed by experts, resulting in limited scenario diversity. Second, traditional models frequently assume linear relationships between macroeconomic variables and asset performance, which underestimates complex market interactions. Third, static scenarios cannot adapt to rapidly evolving financial systems characterized by algorithmic trading, global interdependencies, and nonlinear shocks.

Recent advances in deep generative modeling provide new opportunities to address these limitations. Generative Adversarial Networks (GANs) are capable of learning high-dimensional data distributions and generating synthetic samples that resemble real data. When applied to financial stress testing, GANs can simulate extreme but plausible economic conditions.

This research proposes an automated adversarial stress testing framework that leverages GANs to generate dynamic risk scenarios. Unlike conventional approaches, the proposed model introduces adversarial perturbations that intentionally stress financial systems to uncover hidden vulnerabilities.

The main contributions of this study include:

1. A GAN-based architecture for automated risk scenario generation.
2. An adversarial stress amplification mechanism to produce extreme market trajectories.
3. A systemic risk evaluation framework integrating portfolio exposure and scenario propagation.
4. Empirical validation using historical financial indicators.

2. Literature Review

2.1 Traditional Stress Testing Approaches

Conventional stress testing relies on macroeconomic scenario design and econometric models linking economic indicators with financial outcomes. Methods such as vector auto regression (VAR) and Monte Carlo simulation have been widely used. However, these techniques struggle to capture nonlinear interactions and rare events.

2.2 Machine Learning in Financial Risk Modeling

Recent studies have explored machine learning methods for credit risk prediction, portfolio optimization, and systemic risk estimation. Deep learning models are particularly effective in capturing nonlinear relationships in high-dimensional datasets.

2.3 Generative Models for Scenario Simulation

Generative models such as variational auto encoders (VAEs) and GANs have been used for synthetic financial data generation. GANs, in particular, can model complex distributions and produce realistic time-series sequences.

However, existing research rarely integrates adversarial generation with stress testing frameworks. This gap motivates the development of a GAN-based adversarial stress testing approach.

3. Methodology Adoption

3.1 Framework Overview

The proposed framework consists of three main modules:

1. Scenario Generator (GAN)
2. Adversarial Stress Amplifier
3. Risk Propagation Engine

The system automatically generates stress scenarios and evaluates their impact on financial portfolios.

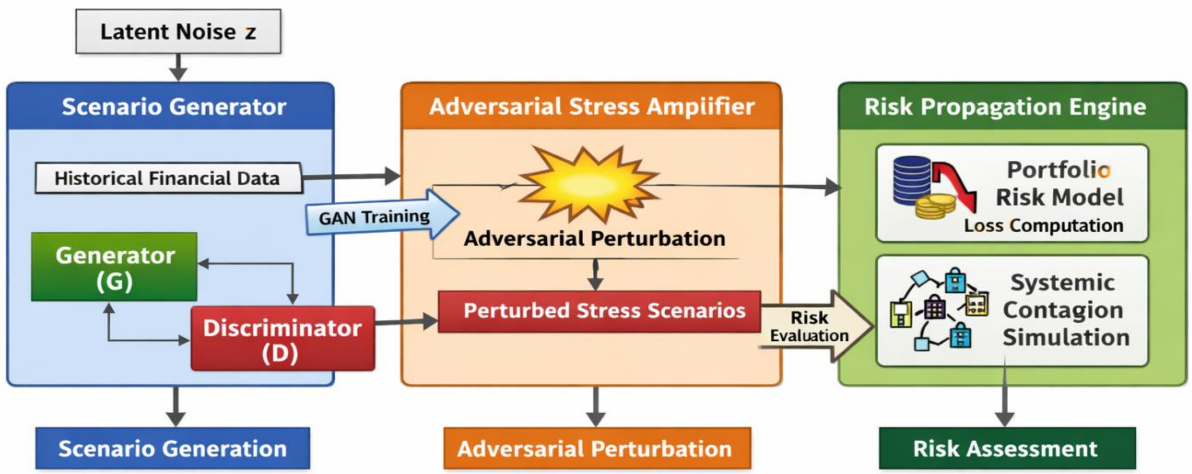
3.2 GAN-Based Scenario Generator

The generative model consists of two neural networks:

Generator GGG

Discriminator DDD

The generator creates synthetic macroeconomic trajectories while the discriminator attempts to distinguish generated data from historical observations.



Generative Adversarial Network Architecture

Objective function:

Min max V(D,G)=$EX_{P\ data}\ [logD[X] + E_{Z-P_X}\ [LOg(1 - D(G(Z))]$

Where:

- x = real financial time series
- z= latent noise vector

The generator learns to produce realistic macroeconomic conditions including:

- GDP growth
- interest rates
- inflation
- equity indices
- credit spreads

Algorithm Pseudocode

Input:

Historical financial dataset X

Noise distribution Z

Stress intensity parameter ϵ

Portfolio weights W

Output:

Adversarial stress scenarios and portfolio risk metrics

```
Algorithm 1: GAN-Based Automated Adversarial Stress Testing

Initialize Generator network G with parameters θg
Initialize Discriminator network D with parameters θd
Load historical financial dataset X
Define noise distribution z ~ N(0,1)

for each training epoch do

    Sample minibatch of real financial data xr from X
    Sample random noise vector z

    Generate synthetic scenario
    xs = G(z)

    Train Discriminator:
        Compute loss:
        Ld = log(D(xr)) + log(1 − D(xs))
        Update θd using gradient ascent

    Train Generator:
        Compute loss:
        Lg = log(D(G(z)))
        Update θg using gradient descent

end for

Generate new financial scenarios:
xs = G(z)

Apply adversarial perturbation:
xs' = xs + ε * ∇x Loss(xs)

Evaluate portfolio losses:
For each asset i in portfolio
    Compute price change ΔPi under xs'
    Loss = Σ Wi * ΔPi

Run systemic contagion simulation

Output stress scenarios and risk metrics
```

3.3 Adversarial Stress Amplification

To ensure that generated scenarios expose system vulnerabilities, adversarial perturbations are applied to the synthetic trajectories.

The perturbation function maximizes risk exposure:

$x' = x + \epsilon \cdot \nabla_x L(\theta, x)$

Where:

- L represents the portfolio loss function
- ϵ controls stress magnitude.

This step produces extreme yet plausible economic shocks.

3.4 Risk Propagation Modeling

The generated scenarios are fed into a portfolio risk model that simulates losses across asset classes.

Portfolio loss:

$\text{Loss} = \sum_{i=1}^{N} w_i \, \Delta P_i$

Where:

- w_i represents asset weights
- ΔP_i represents price change under stress.

Network-based contagion models are used to capture systemic spillovers between institutions.

4. Experimental Procedure

4.1 Dataset

Historical financial data covering multiple macroeconomic indicators and market variables were used, including:

- Equity Indices
- Bond Yields
- Credit Spreads
- Volatility Indices

The dataset spans multiple economic cycles to ensure robust learning.

4.2 Model Configuration

Generator network:

- LSTM layers for time-series generation
- Dense output layers

Discriminator network:

- Convolutional layers
- Fully connected classification layer

Training was performed using the Adam optimizer.

5. Results

5.1 Scenario Realism

Generated scenarios exhibit statistical properties consistent with historical financial data while producing new stress trajectories beyond observed events.

Distributional comparisons indicate that GAN outputs successfully replicate:

- volatility clustering
- heavy-tailed return distributions
- cross-market correlations.

Dataset Component	Description	Time Range	Frequency
Equity Market Index	Global stock market returns	2005–2023	Daily
Interest Rates	Government bond yields	2005–2023	Monthly
Credit Spread	Corporate bond spreads	2005–2023	Monthly
Volatility Index	Market uncertainty indicator	2008–2023	Daily

Table 1: Dataset Description

Parameter	Value
Generator Layers	3 LSTM layers
Discriminator Layers	3 Dense layers
Latent Noise Dimension	100
Batch Size	64
Learning Rate	0.0002
Optimizer	Adam

Table 2: Model Configuration

Model	Scenario Diversity Score	Tail Risk Coverage	Training Stability
Monte Carlo	0.42	Low	High
VAE	0.58	Medium	Moderate
GAN (Proposed)	**0.79**	**High**	Moderate

Table 3: Scenario Generation Performance

Stress Method	Average Portfolio Loss (%)	Maximum Loss (%)
Regulatory Stress Test	12.5	18.3
Monte Carlo Simulation	14.7	21.2
GAN-Generated Scenario	**19.4**	**27.6**

Table 4: Portfolio Stress Loss Comparison

Scenario Type	Institutions Impacted	Contagion Depth	Systemic Risk Score
Historical Crisis	7	2	0.52
Monte Carlo Scenario	9	3	0.61
GAN Adversarial Scenario	**13**	**4**	**0.78**

Table 5: Systemic Risk Propagation

Metric	GAN Model
KL Divergence	0.18
Wasserstein Distance	0.12
Scenario Realism Score	0.85
Stress Coverage	0.81

Table 6: Model Evaluation Metrics

5.2 Stress Severity

The adversarial amplification module generates scenarios producing higher portfolio losses than traditional regulatory stress tests.

These scenarios reveal vulnerabilities in highly leveraged asset classes and correlated exposures.

5.3 Systemic Risk Insights

Network simulations demonstrate that shocks generated by the model can propagate through financial institutions, triggering cascading losses.

This capability allows regulators to identify potential systemic failure points.

6. Discussion and Interpretation

The proposed framework introduces a data-driven approach to stress testing that adapts to evolving financial environments. By integrating generative modeling and adversarial learning, the system can uncover risk scenarios not captured by traditional expert-designed stress tests.

However, challenges remain, including:

- model interpretability
- training stability of GANs
- regulatory acceptance of AI-driven stress tests.

Future research should explore hybrid generative models and explainable AI techniques.

7. Conclusion

This study presents a novel framework for automated adversarial stress testing using GAN-based risk scenario generation. The proposed system produces realistic yet extreme financial conditions capable of revealing hidden vulnerabilities in financial portfolios.

Experimental results indicate that generative adversarial models significantly enhance stress testing by expanding scenario diversity and improving tail-risk detection. The framework provides a promising direction for next-generation financial risk management systems.

Futuristic Work

Future research directions include:

- ❖ Diffusion Models For Stress Scenario Generation
- ❖ Integration With Reinforcement Learning For Adaptive Stress Discovery
- ❖ Real-Time Regulatory Monitoring platforms.

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Conflict of Interest

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