Unveiling the Future, Not Just a Glimpse: Financial Forecasting with Fin-GAN

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A literature review on Fin-GANs

> *Fin-GAN distinguishes itself with its economics-driven loss function and has shown superior performance over traditional forecasting models in financial time series analysis. Its ability to prevent mode collapse and adapt to various datasets makes it an effective tool for producing accurate and diverse predictions in financial forecasting tasks.*

Time series forecasting has long been a holy grail in finance and economics, with applications ranging from trading strategies to risk management. Traditionally, these forecasting tasks have relied on methods that provide only point estimates, lacking the ability to capture the deep uncertainty inherent in financial markets. This shortcoming has motivated researchers to explore more sophisticated techniques that can generate full probability distributions of future outcomes.

Enter Generative Adversarial Networks (GANs) — a powerful class of generative models that have shown promise for probabilistic time series forecasting. Unlike classical approaches, GANs can produce probabilistic forecasts that incorporate uncertainty estimates — a crucial capability for high-stakes applications like portfolio optimization, risk management, and autonomous financial decision-making.

In a recent groundbreaking paper, a team of researchers, Milena Vuletić, Felix Prenzel, and Mihai Cucuringu, introduced a novel GAN-based framework called Fin-GAN that demonstrated impressive results on daily stock and ETF return data. Fin-GAN combines the strength of GANs with the temporal modeling capabilities of recurrent neural networks (RNNs) to generate probabilistic forecasts. But the key innovation was the development of a new economics-driven loss function for training the GAN generator:

$$L^G(\boldsymbol{x}, \hat{\boldsymbol{x}}) = J^{(G)}(\boldsymbol{x}, \hat{\boldsymbol{x}}) - \alpha PnL^*(\boldsymbol{x}, \hat{\boldsymbol{x}}) + \beta MSE(\boldsymbol{x}, \hat{\boldsymbol{x}}) - \gamma SR^*(\boldsymbol{x}, \hat{\boldsymbol{x}}) + \delta STD(\boldsymbol{x}, \hat{\boldsymbol{x}})$$

Economics-driven loss function

"We place Generative Adversarial Networks into a supervised learning setting by introducing a novel economics-based loss function for the generator," the researchers wrote. "Our approach, denoted as Fin-GAN, outperforms a suite of benchmarks on daily stock market data in terms of Sharpe Ratios achieved, while producing distributional forecasts and uncertainty estimates."

The economics-driven loss function is a key innovation that sets Fin-GAN apart. Rather than optimizing the generator solely based on the feedback from the discriminator (as in a standard GAN setup), the researchers introduced additional terms inspired by financial metrics:

- A Profit and Loss (PnL) term that encourages the generator to produce samples aligned with realized PnLs
- A standard deviation term that promotes PnL time series with low volatility
- A Sharpe Ratio term that explicitly optimizes for risk-adjusted returns

"The novel loss function terms do indeed shift the generated distributions, help evade mode collapse, and improve Sharpe Ratio performance," the researchers noted. By placing GANs into this supervised learning setting, Fin-GAN is able to move beyond classical time series forecasting approaches that provide only point estimates.

In comprehensive numerical experiments spanning 31 different stock and ETF datasets, Fin-GAN was compared to standard deep learning methods like LSTMs, classical time series models like ARIMA, and a baseline GAN approach. The results were striking:

- Fin-GAN achieved the highest mean, median and portfolio Sharpe Ratios across all the datasets examined. The median Sharpe Ratio for Fin-GAN was nearly double that of LSTM, the next best performer.
- Fin-GAN generated PnL (profit and loss) time series with significantly lower variance than other models, demonstrating the benefits of its uncertainty-aware approach. The LSTM had higher average PnLs but much more volatility in its forecasts.

- The economics-driven loss function terms were crucial — Fin-GAN outperformed the standard GAN baseline (ForGAN) by a wide margin, highlighting the importance of aligning the model objective with financial goals.
- Fin-GAN was able to achieve competitive Sharpe Ratios even on stocks that were completely unseen during the training process, demonstrating promising "universality" capabilities.

Table 2. Summary of performance metrics over the models across the stocks and ETFs.

	Fin-GAN	ForGAN	LSTM	LSTM-Fin	ARIMA	Long-only
Mean SR	**0.540**	0.033	0.467	0.341	0.206	0.182
Median SR	**0.413**	-0.092	0.214	0.170	0.204	0.194
Portfolio SR	**2.107**	0.172	2.087	0.942	0.612	0.618
Mean PnL	2.978	0.25	**4.123**	2.361	2.059	2.350
Median PnL	1.890	-0.673	1.959	1.735	**2.245**	1.975
Mean MAE	0.044	0.052	0.007	0.007	**0.007**	
Median MAE	0.008	0.009	**0.007**	0.007	0.007	
Mean RMSE	0.049	0.056	0.012	0.012	**0.012**	
Median RMSE	0.012	0.014	0.011	0.011	**0.011**	

Notes: SR refers to the annualized Sharpe Ratio, and PnL refers to the mean daily PnL. MAE and RMSE represent the mean absolute error and the mean root squared error, respectively. Highlighted are the best-performing results according to each metric.

The researchers explored the concept of "universality" — the ability to train on a diverse pool of assets and achieve good performance even on unseen stocks. They found that including sector ETF data in the training process could boost performance, particularly in a focused single-sector setting.

"Even though the universe of stocks was small, we note that good performance is possible even on unseen stocks," the researchers wrote. "Furthermore, performance in the single-sector setting increased when the sector ETF was included in the training data."

This work represents a major advancement in applying generative modeling techniques to financial time series forecasting. By moving beyond point estimates to probabilistic forecasts, Fin-GAN opens up new possibilities for uncertainty-aware decision making in high-stakes financial applications.

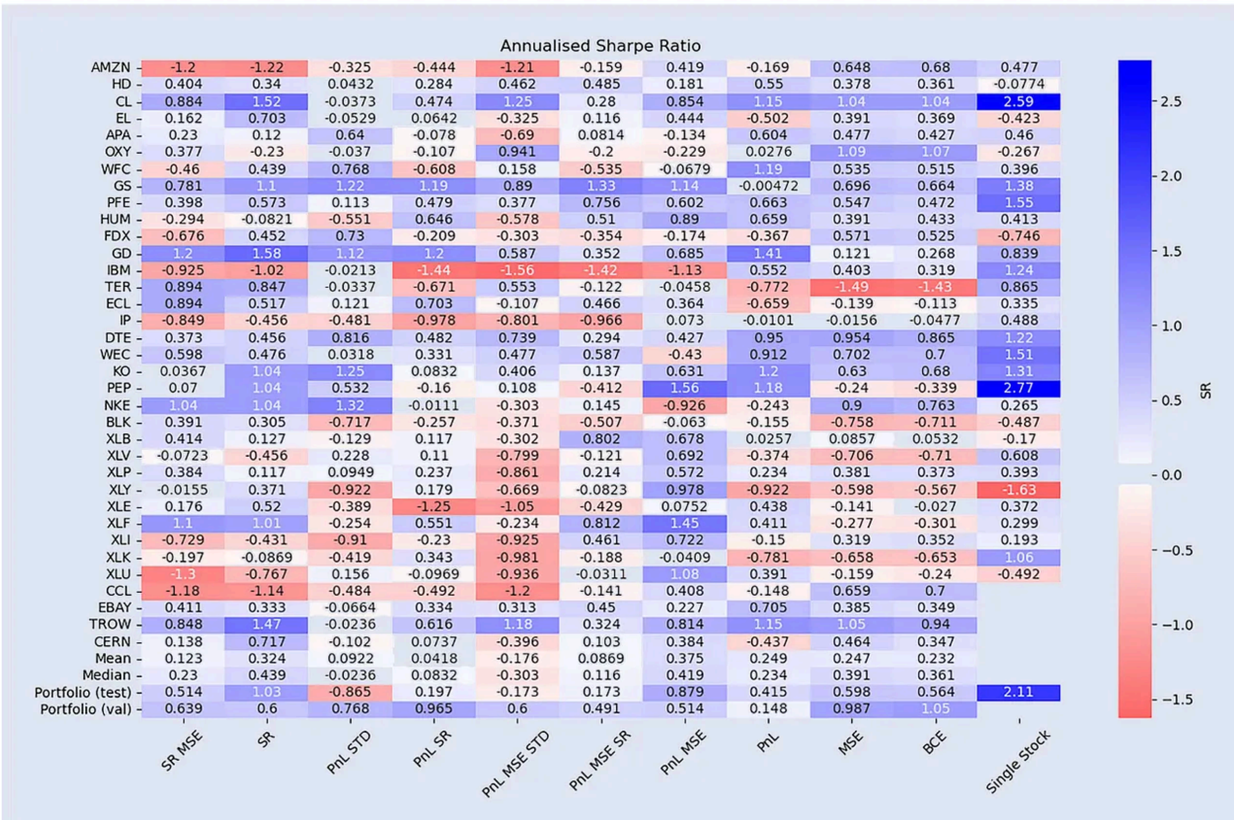

Figure 16. Summary of Sharpe Ratio performance for individual stocks in the universal model. Each column represents a different combination of the loss function terms. The *Single Stock* column shows the best Fin-GAN performance when trained on a particular stock/etf. CCL, EBAY, TROW and CERN have not been seen by the model during the training stage.

The economics-driven loss function is a key innovation that aligns the GAN training process more closely with the objectives of financial practitioners. And the promising results on universality suggest these models may be able to generalize well to new assets and sectors.

As the field of financial machine learning continues to evolve, techniques like Fin-GAN will likely play an increasingly important role. Future research directions include exploring higher-frequency data, cross-asset modeling, and combining Fin-GAN with other advanced GAN architectures. The integration of generative modeling and financial domain knowledge is a powerful frontier worth exploring further.

One area of particular interest is the ability of Fin-GAN to capture the joint co-movements of different assets. The researchers noted that while their experiments only considered individual time series, the potential to model cross-asset interactions could lead to even greater forecasting capabilities.

“We explore the notion of universality, in the spirit of Sirignano and Cont (2019),” the researchers wrote. “We consider 22 different stocks, across different sectors, and 9 sector ETFs, with each industry sector having at least two different stocks included in the training data. We train the networks on the data set created by pooling together the data on all 31 tickers.”

Even with this relatively small universe of assets, Fin-GAN was able to achieve competitive results on unseen stocks, hinting at the potential for more expansive cross-asset modeling. As financial markets become increasingly interconnected, the ability to capture these complex relationships will be crucial.

Another promising avenue for future work is the application of Fin-GAN to higher-frequency data. While the current study focused on daily stock and ETF returns, extending the framework to intraday or even tick-level data could unlock new forecasting opportunities, particularly in domains like algorithmic trading.

The ability of Fin-GAN to generate full probability distributions of future outcomes, rather than just point estimates, opens up a world of possibilities for novel applications in portfolio optimization, risk management, regulatory compliance, and more. GANs could be used to simulate alternative economic scenarios and stress test investment strategies. Or they could be integrated into automated trading systems to dynamically size positions based on predicted uncertainty.

Looking ahead, one can imagine a future where generative models like Fin-GAN become indispensable tools in the arsenal of forward-thinking financial institutions and investors. The power to not only predict future outcomes, but to quantify the associated risks, could revolutionize how decisions are made in an industry where uncertainty is the norm.

But what other disruptive applications might emerge as generative modeling techniques become more sophisticated and widespread in finance? How could the integration of GANs, reinforcement learning, and other advanced AI tools transform portfolio management, trading strategies, and risk mitigation in the years to come?

The ability of models like Fin-GAN to generate probabilistic forecasts opens up exciting new frontiers for financial innovation. As researchers continue to push the boundaries of what's possible with generative modeling, the sky may be the limit in terms of the value these techniques could unlock for the financial industry.

GitHub - milenavuletic/Fin-GAN: Code to accompany the paper "Fin-GAN: Forecasting and Classifying...

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References:

- Milena Vuletić, et al. "Fin-GAN: Forecasting and Classifying Financial Time Series via Generative Adversarial Networks." *Quantitative Finance*, 31 Jan. 2024, pp. 1–25, https://doi.org/10.1080/14697688.2023.2299466.
- milenavuletic. "Milenavuletic/Fin-GAN." *GitHub*, 12 Apr. 2024, github.com/milenavuletic/Fin-GAN. Accessed 17 Apr. 2024.

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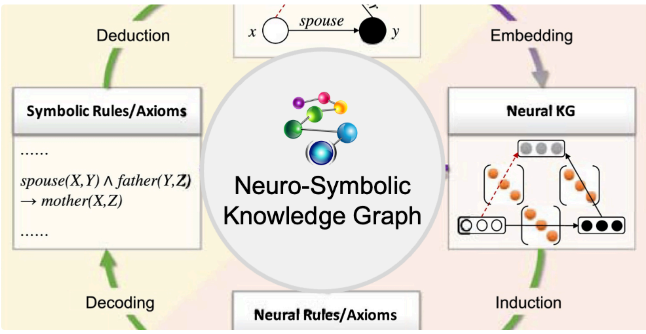

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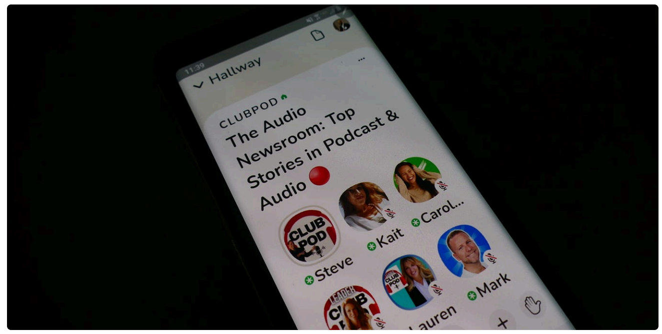

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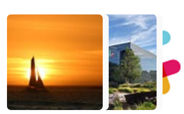

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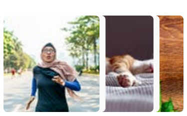

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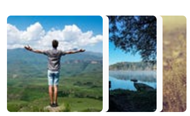

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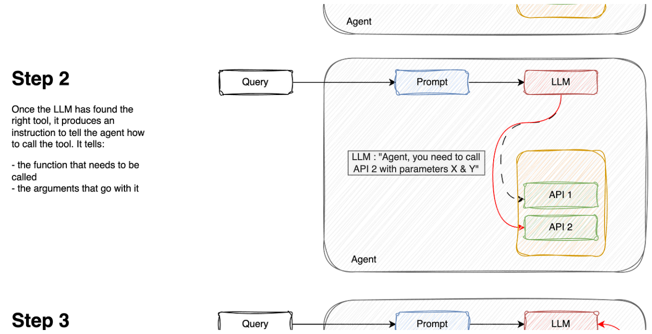

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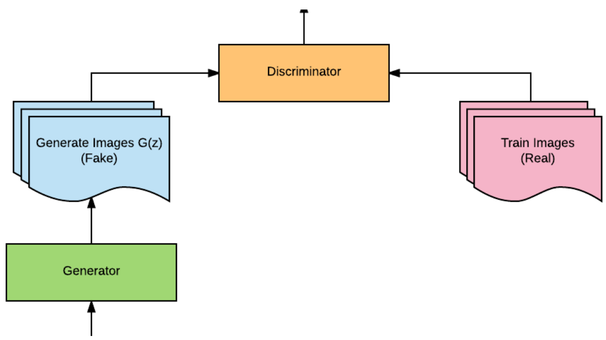

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