(2021) Deep Learning Statistical Arbitrage

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Abstract: *Statistical arbitrage exploits temporal price differences between similar assets. We develop a comprehensive conceptual framework for statistical arbitrage and a novel data driven solution. First, we construct arbitrage portfolios of similar assets as residual portfolios from conditional latent asset pricing factors. Second, we extract their time series signals with a powerful machinelearning time-series solution, a convolutional transformer. Lastly, we use these signals to form an optimal trading policy, that maximizes risk-adjusted returns under constraints. Our comprehensive empirical study on daily US equities shows a high compensation for arbitrageurs to enforce the law of one price. Our arbitrage strategies obtain consistently high out-of-sample mean returns and Sharpe ratios, and substantially outperform all benchmark approaches.*

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📜 Research Core

> Tips: What was done, what problem was solved, background, aims, innovations and shortcomings?

⚙️ Content

The paper focuses on developing a deep learning framework for statistical arbitrage. Statistical arbitrage involves exploiting temporary price differences between similar assets. The authors construct arbitrage portfolios from residuals of conditional latent asset pricing models and apply a deep learning model, particularly a convolutional

neural network (CNN) combined with a transformer, to detect time series signals in these portfolios. They optimize the trading allocation based on these signals, targeting high risk-adjusted returns. The framework is empirically validated on U.S. equity markets, showing significant outperformance of traditional models.

💡 Innovations

1. Introduction of a novel deep learning framework combining CNNs and transformers for statistical arbitrage.
2. The system models arbitrage portfolios using latent factor models and learns temporal patterns without pre-specified filters.
3. The model leverages local and global time-series patterns to enhance the detection of mispricing, outperforming traditional parametric models like Ornstein-Uhlenbeck processes.

🧩 Shortcomings

1. The model heavily relies on data availability and liquidity, which limits its application to the most liquid assets.
2. Despite its high performance, the complexity of the CNN-Transformer model might make real-time trading difficult due to computation time and transaction costs.

🔁 Research Content

💧 Data

The authors used daily U.S. equity returns from the CRSP dataset, focusing on the most liquid stocks from 1998 to 2016. They also utilized firm-specific characteristics to construct conditional latent factor models.

👩🏻‍💻 Method

1. **Portfolio Construction**: Arbitrage portfolios are created using residuals from latent factor models like Instrumented Principal Component Analysis (IPCA) and Fama-French models.
2. **Signal Extraction**: Time-series signals are extracted using a CNN and transformer

architecture, which identifies local and global patterns in the data.

3. **Trading Allocation**: The trading allocation function maximizes the Sharpe ratio or expected returns using a feedforward neural network, based on the extracted signals.

🔬 Experiment

The model is tested on a rolling window basis, simulating real-world trading conditions. It is compared against benchmarks like traditional arbitrage models (e.g., Ornstein-Uhlenbeck). The authors find that their model consistently achieves higher Sharpe ratios and returns out-of-sample.

📜 Conclusion

The deep learning model significantly outperforms traditional statistical arbitrage models. It highlights the importance of flexible time-series modeling, demonstrating that machine learning models optimized for trading objectives (rather than just prediction) can uncover valuable signals for arbitrage strategies.

🧐 Personal Summary

> Tips: What aspects did you question, how do you think it can be improved?

🙋‍♀️ Key Records

1. The model's success in extracting non-linear temporal dependencies using CNN and transformer methods.
2. Empirical results showing Sharpe ratios above 4.0 and out-of-sample mean returns of 20% annually.
3. The importance of integrating firm-specific characteristics into the latent factor models.

📌 To be resolved

1. Scalability: The high complexity of the model could make it difficult to implement in real-time trading systems.
2. Broader Asset Classes: Extending the model to less liquid assets or other asset

classes (e.g., bonds, cryptocurrencies) could enhance its applicability.

💭 Thought Inspiration

The study suggests that using deep learning for statistical arbitrage is a promising direction. It challenges traditional approaches by showing the value of machine learning in extracting and trading based on complex time-series patterns. This raises the question of whether other AI models, such as reinforcement learning, could further enhance trading strategies by optimizing for different financial environments or incorporating dynamic market conditions.