MSCF
Master of Science in Computational Finance

Carnegie Mellon University
Statistics & Data Science

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Mid-Semester Research Progress Report: Neural Networks for Option Pricing

Current Focus: Replication and Extension of Neural Network Architectures for Black-Scholes Option Pricing

Reference: In our research we replicate the "synthetic" portions of the below paper.

Machine learning for option pricing: an empirical investigation of network architectures

I. Environment and Infrastructure Setup: We began by establishing a robust development environment, including drive mounting, necessary library installations (such as SciPy with QMC), reproducible global seeding, and a comprehensive run logging system. This infrastructure supports organized experiment tracking and includes a checkpointing and resume feature for training, ensuring continuity.

II. Black-Scholes Model Fundamentals and Scaling: We successfully implemented and verified the Black-Scholes European call option formula in both its direct pricing and scaled forms (using moneyness S/K and time-to-maturity tau). Visualizations helped explore the relationships of call price with spot price, moneyness, and volatility, laying a clear foundation.

III. Synthetic Dataset Generation via Latin Hypercube Sampling: A major milestone involved generating a dataset of one million synthetic Black-Scholes European call option contracts. We used Latin Hypercube Sampling (LHS) for the input parameters (moneyness, tau, interest rate r, and volatility sigma) to ensure uniform coverage across the input domain. Corresponding scaled option prices (V/K) were calculated, and thorough sanity checks confirmed data validity and no-arbitrage conditions. Histograms and scatterplots validated the LHS distribution.

IV. Neural Network Architecture Benchmarking (Black-Scholes ANN): Our core work involves benchmarking Multilayer Perceptrons (MLPs) for option pricing. Key achievements include:

- **Learning Rate Range Test:** We conducted an extensive learning rate range test across 12 MLP architectures to identify optimal learning rate intervals.
- **Comprehensive Architecture Sweep (100k Dataset):** We trained and evaluated 12 MLP architectures on 100,000 data samples, recording training times and final test Mean Squared Error (MSE), to analyze the trade-offs between computational cost and accuracy.
- **Full Dataset Training and Scaling Analysis (1M Dataset):** We continued the training process by benchmarking four key architectures using the full 1 million data points. A comparison showed expected increases in training time and significant improvements in test MSE with the larger dataset.
- **Paper-Exact Evaluation Structure:** For direct comparison with research literature, we implemented a data split of 800,000 for training, 200,000 for validation, and a separate 100,000 for testing, confirming consistent performance under these controlled conditions for two representative models.

V. Accomplished Components of Overarching Research Scope: We have substantially completed:

- "generating one million synthetic contracts using Latin Hypercube Sampling"
- "benchmarking multiple architectures on accuracy (MSE) and computational efficiency" (specifically for Black-Scholes)
- "conduct controlled train/validation/test experiments" (for Black-Scholes)
- "analyzing architectural trade-offs under fixed parameter budgets" (for Black-Scholes)

VI. Future Plans:

- Transition to noisy, real-world OptionMetrics market data, accessed via Wharton Research Data Services (WRDS).
- Apply the established architecture benchmarking task to this noisier environment to evaluate model robustness and performance on actual market implied volatility surfaces.
- Extend the framework to more complex option pricing models like Heston and explore direct implied volatility tasks.

VII. Research Logistics and Collaboration: This research is a collaborative effort led by MSCF Professor Chad Schafer at Carnegie Mellon University, with significant contributions from research assistants Joseph Ouyang and Caleb Ouyang. Our team holds bi-weekly meetings to discuss training results, review code implementations, and ensure architecture consistency across experiments. To maintain accountability and track progress, weekly email reports are scheduled and submitted.

This robust foundation positions us to further understand neural network effectiveness in diverse financial modeling scenarios.