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Allocation Of Stocks In The Portfolio Using Puma Optimizer

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Abstract
Portfolio optimization plays a vital role in financial decision-making by strategically allocating assets to maximize returns while minimizing risk. Conventional approaches, such as Markowitz's mean-variance model, face challenges in managing complex, high-dimensional, and multimodal financial markets. To overcome these limitations, nature-inspired metaheuristic algorithms like the Puma Optimizer provide effective alternatives. The Puma Optimizer is a novel metaheuristic optimization algorithm inspired by the behavior and intelligence of pumas (also known as cougars or mountain lions). It is specifically designed for global optimization tasks and demonstrates high performance across various benchmark functions and machine learning problems. Two sets of portfolio consisting of 15 and 30 stocks have been considered. Efficient frontiers in two cases have been plotted and the results obtained are satisfactory.

Keywords: Portfolio Optimization, Puma Optimizer, Financial Markets

1. Introduction

Creating a portfolio that meets investors' objectives is essentially an optimization challenge. In such problems, it is crucial to determine the ideal stock weightings that reduce risk while enhancing returns.
Collectively, various studies [2-15]] not only demonstrate significant improvements in handling constraints, risk, and computational complexity, but also pave the way for future research.

2. Puma Optimizer for Portfolio Optimization

The Puma Optimizer mimics various aspects of the behavior and lifestyle of the puma, also known as the cougar or mountain lion. Pumas are solitary ambush predators with large territorial ranges. They use a combination of strategic memory, territorial patrolling, ambushing, and sprinting to capture prey. These behaviors are abstracted and translated into algorithmic mechanisms to guide a population of candidate solutions (agents) through the optimization process. The best agent in the population is likened to the dominant male puma, while the remaining agents represent females navigating and learning from the territory**.** More details about Puma optimizer are available in [1].

The mathematical formulation of PO is comprehensive. It incorporates:

- Cost function evaluations to monitor fitness improvements
- Time-adjusted scoring metrics to assess exploration and exploitation effectiveness
- Adaptive control parameters that shift dynamically during the search process
- Mechanisms to balance intensification and diversification using well-defined equations

This detailed modeling ensures that the algorithm remains robust, scalable, and theoretically sound across different types of optimization landscapes.

3. Application and Results

The stocks of the top 100 companies listed on the Bombay Stock Exchange (BSE) were selected based on their market capitalization and financial investments within specific sub-categories. Data on the monthly stock returns from January 2009 to February 2015 were obtained from the financial website www.moneycontrol.com. Two portfolios, consisting of 15 and 30 were optimized using the Puma Optimization technique. Dataset available in [16].

Consider a portfolio consisting of 15 stocks. Figure 1 shows this case's convergence characteristics for PO. It can be observed that POtook around 850 iterations for convergence. Figure 2 presents the efficient frontier obtained using this technique for the problem. A few samples are given from the simulation set-up in Table 1. Consider a portfolio consisting of 30 stocks with a higher level of diversification complexity than the previous case. The convergence characteristics for PO for this portfolio are shown in Figure 3.

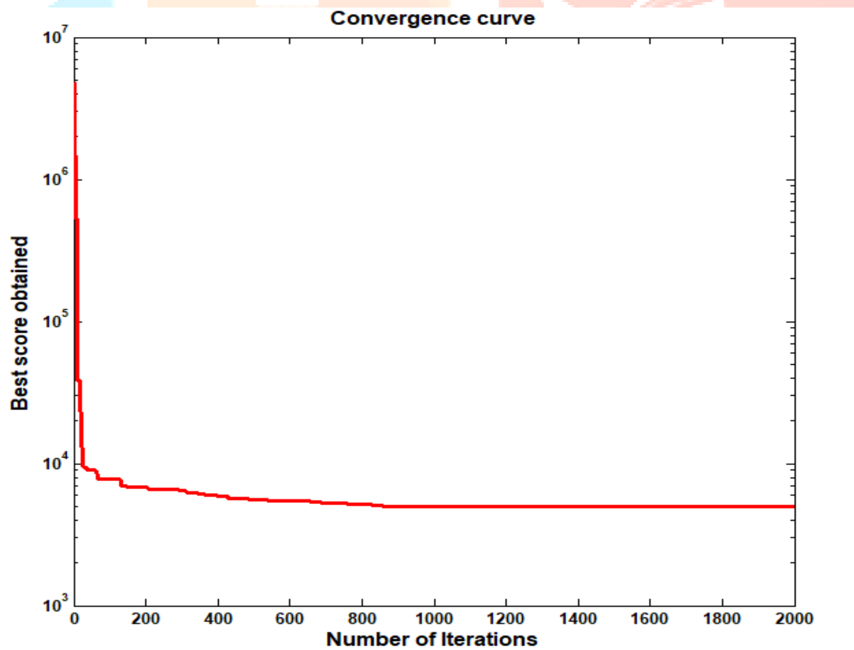

Figure 1. Convergence characteristics of POfor a portfolio consisting of 15 stocks

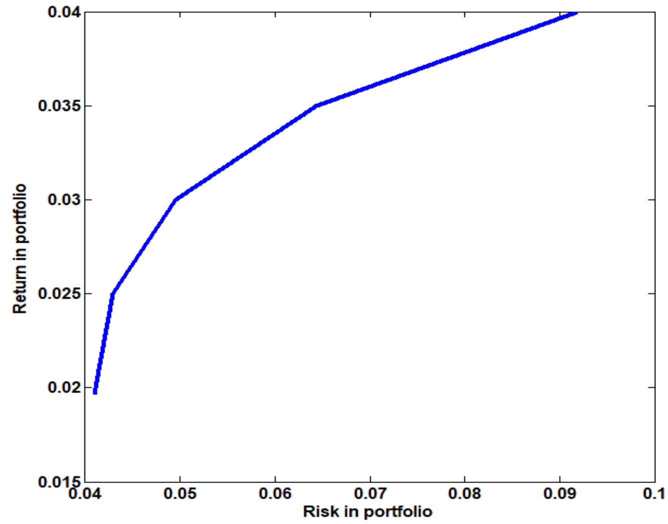

Figure 2. Efficient Frontiers were obtained using PO for a portfolio of 15 stocks

Table 1. Comparative Results for a portfolio consisting of 15 stocks

Target Return(samples)		
0.01	Optimal weights $\Sigma w_i = 1$	0.1055 0.0758 0.0283 0.2011 0 0.1083 0.0000 0.0000 0.2240 0.0000 0.1214 0.1354 0.0000 0.0000 0
	Return and Risk	Return = 0.0196 and Risk = 0.0411
0.015	Optimal weights $\Sigma w_i = 1$	0.1059 0.0754 0.0290 0.2012 0.0000 0.1079 0.0000 0 0.2236 0.0000 0.1213 0.1355 0.0000 0.0000 0.0000
	Return and Risk	Return= 0.0196 and Risk = 0.0411
0.02	Optimal weights $\Sigma w_i = 1$	0.1165 0.0659 0.0357 0.1940 0.0000 0.1022 0.0000 0.0000 0.2239 0.0000 0.1219 0.1396 0 0.0000 0.0000
	Return and Risk	Return= 0.0200 and Risk = 0.0411
0.025	Optimal weights $\Sigma w_i = 1$	0.2625 0 0.1022 0.0895 0.0000 0.0105 0.0000 0.0000 0.2298 0.0000 0.1019 0.2036 0.0000 0 0.0000
	Return and Risk	Return= 0.0250 and Risk = 0.0429
0.03	Optimal weights $\Sigma w_i = 1$	0.3658 0.0000 0.0091 0 0.0000 0.0000 0 0.0000 0.2013 0.0000 0.0074 0.2937 0.0000 0.0000 0.1226

	Return and Risk	Return= 0.0300 and Risk = 0.0495
0.035	Optimal weights $\Sigma w_i = 1$	0.5001 0 0.0000 0.0000 0.0000 0 0.0000 00 0.0000 0.0000 0.2689 0.0000 0.1347 0.0968
	Return and Risk	Return= 0.0350 and Risk = 0.0643
0.04	Optimal weights $\Sigma w_i = 1$	0.4848 0 0 0 0 0 0 0 0.0000 0.0000 0.0000 0.0000 0 0.5163 0
	Return and Risk	Return= 0.0400 and Risk = 0.0919

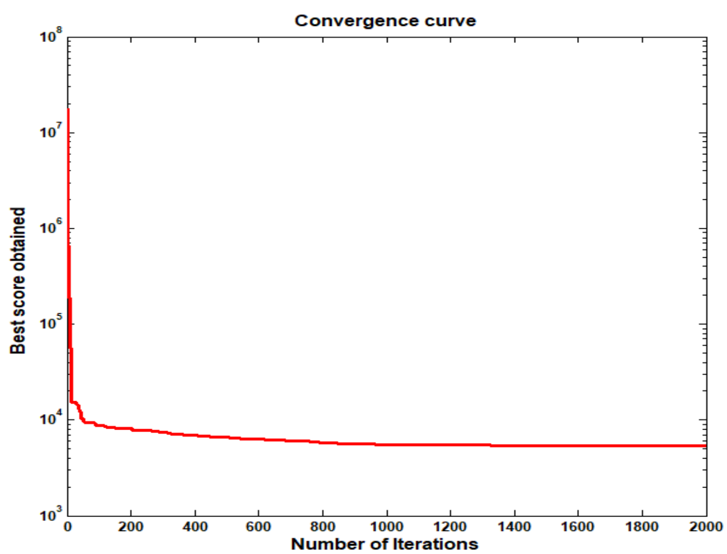

Figure 3. Convergence characteristics of PO for a portfolio consisting of 30 stocks

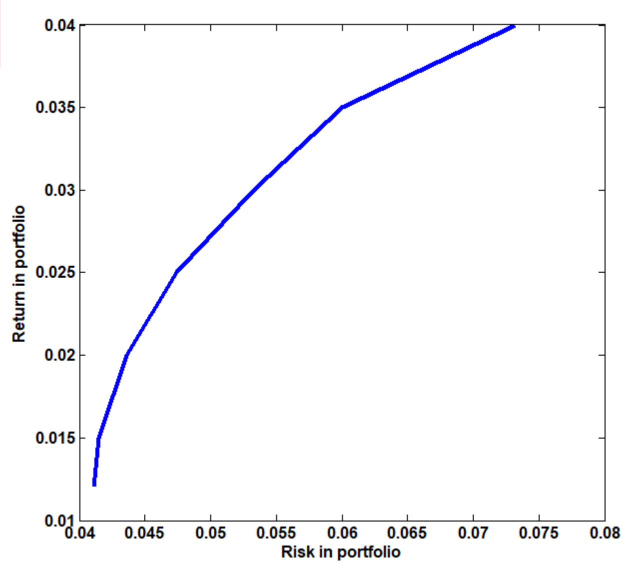

Figure 4. Efficient Frontiers were obtained using PO for a portfolio of 30 stocks.

Conclusion:

The Puma Optimizer is a bio-inspired, population-based metaheuristic algorithm that mimics the hunting intelligence, territorial memory, and adaptive movement of pumas. It is designed to efficiently solve global optimization problems by balancing exploration and exploitation through a novel phase-change mechanism grounded in puma behavior. This paper presents the implementation and evaluation of the Puma Optimizer in the context of portfolio optimization. The study provides valuable insights into both the theoretical development of PO and its practical applications in financial markets. Two cases that of 15 and 30 stocks have been considered and optimized. The Puma Optimizer is a remarkable example of how natural behavior can be abstracted to design sophisticated computational algorithms. By emulating the territorial intelligence and adaptive hunting strategies of pumas, PO provides a powerful tool for solving complex optimization problems. Its dynamic phase-switching mechanism ensures a balanced search, while its performance on benchmarks and real-world tasks validates its practical utility. As optimization problems grow in complexity, algorithms like the Puma Optimizer represent the future of adaptive, intelligent computation. Future investigation could be combining Puma Optimizer with artificial intelligence (AI) and machine learning (ML) techniques.

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