

Financial Asset Recommendation

Comparing the Performance of collaborative filtering, contextual and non-contextual bandit algorithms

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AGENDA



Introduction

Collaborative Filtering

Why Multi Armed Bandit?

Contextual Multi Armed Bandit

Dataset

Experimental Setup

Results

Conclusion



INTRODUCTION

- A data-driven system that suggests optimal financial assets (e.g., stocks, funds, ETFs, bonds) for individual investors.
- The most common way of recommending a financial asset is through traditional risk-based portfolio allocation, where assets are suggested based on an investor's risk profile using rule-based or mean-variance (Markowitz) portfolio optimization methods.
- **Impact of FAR:**
 - Better Portfolio Performance
 - Customer Satisfaction
 - Minimizes emotional decision-making

Choose the best model for financial asset recommendation



Collaborative Filtering

Effective for interaction-based recommendation



Multi Armed Bandit

Suitable for merit-based recommendation

CHALLENGES

- Market volatility makes asset returns highly unpredictable.
- Hard to get real-world data
- Investor preferences and risk profiles vary widely and change over time.
- Sparse or limited historical interaction data reduces recommendation accuracy.
- Different assets have different liquidity and risk characteristics, making comparison difficult.
- Feedback is delayed because true reward is known only after days/weeks.

Collaborative Filtering

Why Multi Armed Bandit

Contextual Multi Armed Bandit

DATASET



MAB Data STRUCTURE



EXPERIMENTAL SETUP

EVALUATION METRICS

- **Regret:** Regret tells you how much worse your algorithm performed compared to a perfect oracle that always picks the best asset

RESULTS



CONCLUSION



FEEDBACK!
