

# Stock price simulation using Machine Learning and GBM

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# Introduction

The answer to the question, what will be the stock price in the specific time in the future is worth a fortune. Investors around the globe are seeking to know what the evolution of their stocks is in the future.

Monte Carlo simulation offers a powerful approach to anticipating future stock price fluctuations. This practical work focuses on applying this method and Linear Regression method to Microsoft to assess the potential variability of its stock prices.

# Data and methodology

## GBM

$$dV(t) = \mu V(t)dt + \sigma V(t)dB(t) \quad (1)$$

$$V(t) = v_0 e^{(\mu - \frac{1}{2}\sigma^2)t + \sigma B(t)} \quad (2)$$

# Data and methodology

## Data

The data used is historical Microsoft stock price data. The period considered extends from 2020-01-01 to 2023-10-01.

Date	Open	High	Low	Close	Volume	Next_close	Daily yield (%)
2020-01-02 00:00:00-05:00	153.006435	154.885527	152.572801	154.779526	22622100	152.852280	-1.245156
2020-01-03 00:00:00-05:00	152.563200	154.133920	152.312645	152.852280	21116200	153.247360	0.258472
2020-01-06 00:00:00-05:00	151.368269	153.314822	150.818988	153.247360	20813700	151.850052	-0.911799
2020-01-07 00:00:00-05:00	153.526787	153.864051	151.599511	151.850052	21634100	154.268829	1.592872
2020-01-08 00:00:00-05:00	153.151006	154.953019	152.206644	154.268829	27746500	156.196091	1.249288

Figure: DATA

# Data and methodology

## Methodology

### Monte Carlo simulation

$$\text{Price}_i = \text{Price}_{i-1} \cdot e^{(\mu - \frac{1}{2}\sigma^2) + \sigma \cdot Z(\text{Rand}(0,1))} \quad (3)$$

$$\text{Drift} = \mu - \frac{1}{2}\sigma^2$$

$$\text{Shock} = \sigma * Z(\text{Rand}(0; 1))$$

# Data and methodology

## Methodology

### Linear Regression

	Open	High	Low	Close	Volume	Next_close
Open	1.000000	0.998844	0.998769	0.997171	-0.343700	0.993409
High	0.998844	1.000000	0.998445	0.998646	-0.326870	0.994699
Low	0.998769	0.998445	1.000000	0.998711	-0.363338	0.994800
Close	0.997171	0.998646	0.998711	1.000000	-0.346846	0.995486
Volume	-0.343700	-0.326870	-0.363338	-0.346846	1.000000	-0.344967
Next_close	0.993409	0.994699	0.994800	0.995486	-0.344967	1.000000

Figure: Correlation table

# Expected results and discussion

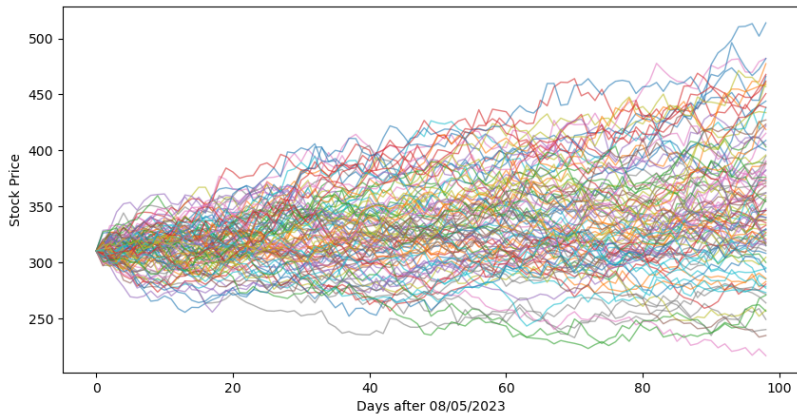


Figure: Monte Carlo Simulation



# Expected results and discussion

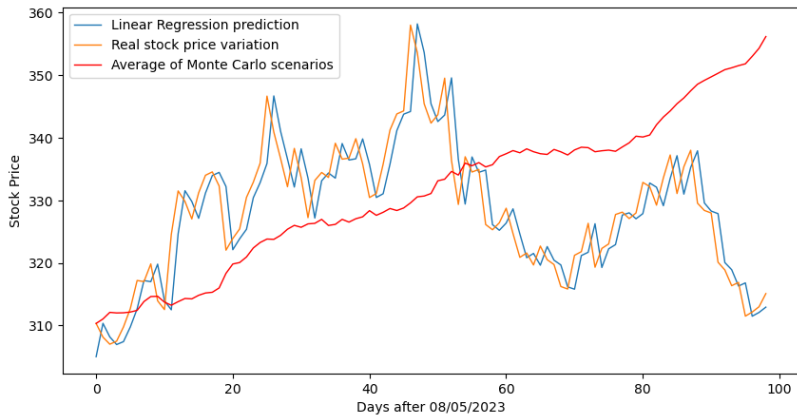


Figure: Linear Regression and Monte Carlo

# Implications and applications

- Portfolio Management
- Option Pricing
- Investment Decision-Making



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# Conclusion and Perspectives

This study demonstrates the feasibility of addressing financial sector gaps, particularly in the stock market, through Monte Carlo simulation with Geometric Brownian Motion as the underlying stock price model. While the method offers an overview of trends rather than exact prices, linear regression was employed to validate the trends. Monte Carlo predictions align with trends but lack the precision of linear regression. A potential solution could involve a model combining linear regression and GBM to account for both deterministic and random aspects of prices.

# Conclusion and Perspectives

## Perspectives

- **Enhanced Risk Management:** Integrating ML and Monte Carlo simulations enhances risk management strategies.
- **Portfolio Optimization:** The model's predictive capabilities can contribute to optimizing investment portfolios.