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PREDICTING GOLD MARKET TRENDS USING NEWTON'S DIVIDED DIFFERENCE METHOD

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Abstract

Gold is a vital financial asset often used as a hedge in times of economic instability. This study explores the application of Newton's Divided Difference (NDD) method to forecast gold market trends using historical price data from March 2022 to April 2025. Both monthly (36 data points) and quarterly (12 data points) datasets were analyzed to assess the impact of data resolution on model accuracy and efficiency. Polynomial interpolation models of degree 3 and 7 were constructed using Newton's Forward and Backward Divided Difference techniques. Error metrics such as Absolute Error (AE) and Percentage Absolute Relative Error (PARE) were used to evaluate prediction accuracy. The results revealed that while monthly data offered finer detail, quarterly data produced more stable and interpretable forecasts. This study confirms that NDD is a practical method for financial trend prediction, offering a simple yet effective alternative to more complex algorithms.

Keywords*:* Gold price prediction, Newton's Divided Difference, interpolation, polynomial modeling, data frequency comparison

Introduction

Gold is a widely traded commodity and a safe-haven asset, especially during periods of economic uncertainty. Accurate forecasting of gold prices is essential for investors, financial analysts, and policymakers. Traditional prediction methods often rely on large datasets and complex machine learning models. This study aims to investigate a simpler yet powerful classical technique which is Newton's Divided Difference (NDD) interpolation for modeling and predicting gold price trends. Newton's Divided Difference is a classic numerical interpolation technique effective for handling unevenly spaced data points. Prior studies highlight its accuracy and computational simplicity, particularly in fields where data is limited but time-sensitive, such as financial forecasting. This work builds on such findings by evaluating NDD's effectiveness in predicting real-world gold price trends.

Background

Gold is a principal safe-haven asset, especially in times of economic and geopolitical uncertainty. Forecasting gold prices is crucial for informed financial decision-making [1]. Traditional forecasting models rely on complex algorithms and big data, making them less accessible [2],[3]. This study investigates NDD, a venerable numerical interpolation method valued for its ease of use and appropriateness to handle unevenly spaced data [3],[4]. Gold prices between March 2022 and April 2025 were analyzed in terms of datasets by month and quarter. Order 3 and 7 polynomial models were constructed by way of forward and backward NDD methodologies. The purpose is to analyze the practicability and validity of NDD in predicting actual gold prices.

Methodology

The methodology of this study uses the historical gold price data from March 2022 to April 2025 collected from a reputable financial source and organized into two distinct datasets: monthly data containing 36 data points and quarterly data comprising 12 data points. Figure 1 below shows the source of the data from MSN Finance [5].

Figure 1: Gold Price from March 2022 – April 2025

For each dataset, a Newton's Divided Difference (NDD) table was created to build the interpolation polynomials. These tables display the gold price values along with their divided differences, calculated step by step up to the highest order. Table 1 illustrates this pyramid structure of the NDD table using the 12 data points.

Table 1: NDD Table

x_i	$f(x_i)$	$1^{st} DD$	$2^{nd} DD$	$3^{rd} DD$	$4^{th} DD$	$5^{th} DD$	$6^{th} DD$	$7^{th} DD$	$8^{th} DD$
0	1943.80								
		-31.7000							
3	1848.70		-2.4611						
		-46.4667		1.7006					
6	1709.30		12.8444		-0.2803				
		30.6000		-1.6636		0.0316			
9	1801.10		-2.1278		0.1943		-0.0031		
		17.8333		0.6679		-0.0237		0.0003	
12	1854.60		3.8833		-0.1607		0.0028		0.0000
		41.1333		-1.2605		0.0269		-0.0003	
15	1978.00		-7.4611		0.2428		-0.0034		0.0000
		-3.6333		1.6531		-0.0339		0.0004	
18	1967.10		7.4167		-0.2664		0.0041		0.0000
		40.8667		-1.5438		0.0395		-0.0004	
21	2089.70		-6.4778		0.3263		-0.0049		0.0000
		2.0000		2.3716		-0.0482		0.0005	
24	2095.70		14.8667		-0.3970		0.0051		
		91.2000		-2.3920		0.0432			
27	2369.30		-6.6611		0.2516				
		51.2333		0.6278					
30	2523.00		-1.0111						
		45.1667							
33	2658.50								

Newton's Forward Divided Difference

Newton's Backward Divided Difference

A similar derivation process was also carried out for the full dataset comprising 36 data points to obtain a more comprehensive interpolation. The resulting polynomial formulas derived from both datasets are presented as follows.

Polynomial equations of degree 3 and degree 7 (Monthly Data/All data):

NFDD:

$$P_3(x) = 1943.80 + 28.3x - 62.6x^2 + 14.2x^3 \quad (1)$$

$$P_7(x) = 1943.80 + 420.424x - 958.7658x^2 + 759.9459x^3 - 296.6702x^4 + 61.0432x^5 - 6.338 + 0.2613x^7 \quad (2)$$

NBDD:

$$P_3(x) = 2857.10 - 302.3666x + 126.9999x^2 - 12.7333x^3 \quad (3)$$

$$P_7(x) = 2857.10 - 68.9816x - 367.9796x^2 + 348.6684x^3 - 115.1657x^4 + 16.2047x^5 - 0.849 + 0.003x^7 \quad (4)$$

Polynomial equations of degree 3 and degree 7 (Quarterly Data):

NFDD:

$$P_3(x) = 1943.80 + 6.2941x - 17.7665x^2 + 1.7006x^3 \quad (5)$$

$$P_7(x) = 1943.80 + 360.9931x - 285.5732x^2 + 74.9957x^3 - 9.5533x^4 + 0.6436x^5 - 0.022x^6 + 0.0003x^7 \quad (6)$$

NBDD:

$$P_3(x) = 2658.50 - 53.4338x + 4.6391x^2 - 0.6278x^3 \quad (7)$$

$$P_7(x) = 2658.50 - 589.3298x + 415.3829x^2 - 115.5191x^3 + 15.3716x^4 - 1.0602x^5 + 0.0366 - 0.0005x^7 \quad (8)$$

To model and forecast future prices, both Newton's Forward Divided Difference (NFDD) and Backward Divided Difference (NBDD) interpolation techniques were applied to each dataset. Polynomial models of degree 3 and 7 were constructed using Maple software. The performance of each model was assessed using Absolute Error (AE) and Percentage Absolute Relative Error (PARE) as evaluation metrics.

Results

Table 2 below shows the results of comparison of both NFDD and NBDD methods by using monthly data.

Table 2: Comparison of NFDD and NBDD for Monthly Data

x_i	DEGREE 3				DEGREE 7			
	AE		PARE		AE		PARE	
	NFDD	NBDD	NFDD	NBDD	NFDD	NBDD	NFDD	NBDD
1	0	745.30	0	38.7430	0	745.30	0	38.7430
5	507.60	1140.9020	28.3940	63.8195	0.0012	735.3020	0.0001	41.1312
15	34230.30	18056.3090	1730.5511	912.8569	6138335.5462	1591355.3090	310330.4118	80452.7457
19	75433.50	46225.8062	4083.6672	2502.4798	52734161.6746	9895439.4830	2854816.0283	535699.4090
22	121396.20	79984.5920	5854.9339	3857.6537	185862928.0695	28730551.4600	8964161.6702	1385673.3607

A comparison between degree 3 and degree 7 polynomial models using NFDD and NBDD approaches reveals significant differences in performance. Degree 3 model shows reliable and consistent error growth on both approaches, which implies enhanced reliability for interpolation of monthly data. Degree 7 model produces very low error at interpolation points but a sharp increase at boundary values, especially with NFDD. This is Runge's phenomenon, and it indicates the instability of higher-degree polynomials. Generally, the degree 3 model is easier and reliable for practical use. Table 3 below shows the comparison of NFDD and NBDD methods using quarterly data for both degree 3 and degree 7 polynomial interpolation models.

Table 3: Comparison of NFDD And NBDD for Quarterly Data

x_i	DEGREE 3				DEGREE 7			
	AE		PARE		AE		PARE	
	NFDD	NBDD	NFDD	NBDD	NFDD	NBDD	NFDD	NBDD
1	10.3282	685.3775	0.5369	35.6281	161.5842	459.6815	8.3997	23.8957
5	44.0170	641.1335	2.4622	35.8636	83.6770	695.7735	4.6807	38.9200
15	1802.2740	1196.0345	91.1160	60.4669	0.7860	10.1945	0.0397	0.5154
19	5466.8968	2835.3073	295.9559	153.4922	32.8968	247.2527	1.7809	13.3853
22	9517.8730	5029.9336	459.0466	242.5935	1058.2218	1847.7832	51.0380	89.1185

A performance comparison between degree 3 and degree 7 polynomial interpolation models using NFDD and NBDD reveals distinct differences. The degree 3 model, particularly when applied with NFDD, yields more stable and consistent results with gradual error progression. In contrast, the degree 7 model achieves higher accuracy at central data points but exhibits significant boundary errors, especially under the NBDD method. These findings suggest that degree 3 with NFDD offers a more robust and balanced approach for gold price forecasting based on quarterly data. Figure 2 shows the comparison between actual monthly gold prices and the forecasts generated using degree 3 and degree 7 polynomial models.

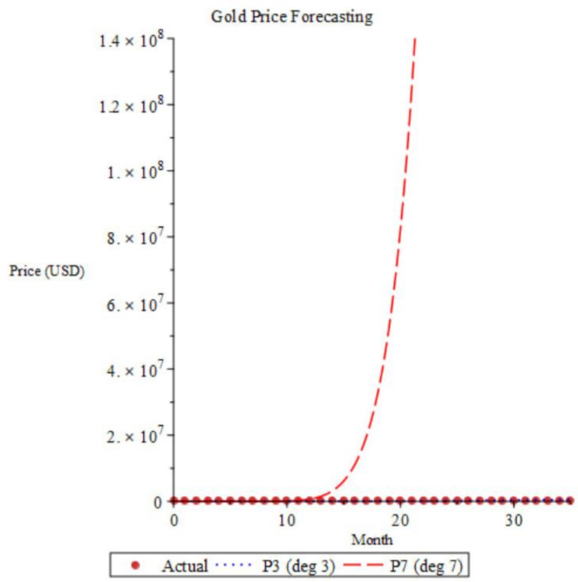

Figure 2: Graph Gold Price Forecasting (Monthly Data)

The graph is a comparison of real gold prices and those that are forecast by degree 3 and degree 7 polynomial models. The degree 3 model follows the real trend quite closely with smooth and stable outcomes over the course of the period. In contrast, the degree 7 model starts to deviate significantly after a certain point, showing sharp increases that do not match the real data This indicates that higher-order models may lead to overfitting and less precise predictions, especially near the extremes of the data set. Figure 3 below shows the comparison between actual quarterly gold prices with the predicted values from degree 3 and degree 7 polynomial models.

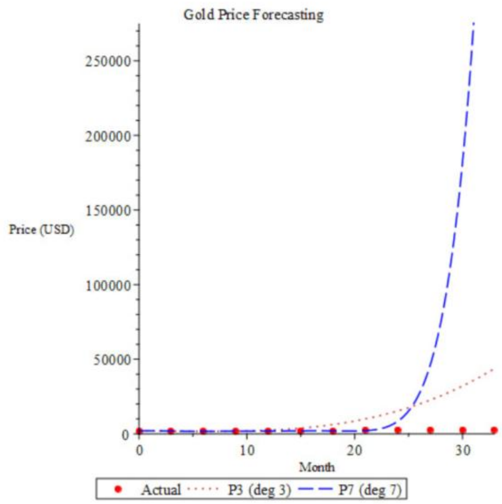

Figure 3: Graph Gold Price Forecasting (Quarterly Data)

This graph compares actual quarterly gold prices with predicted values generated by degree 3 and degree 7 polynomial models using NDD method. Both models initially follow the actual trend closely, but as the time progresses, the degree 3 model maintains a stable and realistic curve, while the degree 7 model shows a sharp increase and deviates significantly from the actual data. This highlights the risk of overfitting and instability in higher-degree models when applied to lower-frequency datasets.

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