Naive Forecasting in Excel: Step-by-Step Example

Authored by

Mohammed looti

November 6, 2025

In the world of business intelligence and data science, predicting future outcomes is essential for strategic planning. One of the most straightforward and often surprisingly effective methods for time-series prediction is the Naive Forecast. This technique serves as a fundamental baseline model against which more complex models are measured.

A **naive forecast** operates on a very simple premise: the forecast for any given future period is defined solely by the actual value observed in the immediately preceding period. If sales were 100 units in March, the naive forecast suggests sales will also be 100 units in April. While seemingly too simple, this method is invaluable for initial analysis and establishing performance benchmarks, particularly when dealing with data that exhibits random walk characteristics.

Understanding the Naive Forecasting Principle

To grasp this concept, consider a practical example involving monthly sales figures. Suppose a company tracks its product sales over the first quarter of the year. The principle dictates that the prediction for the next month simply echoes the performance of the last recorded month.

For instance, examine the following initial sales data:

Month	Actual Sales
January	34
February	37
March	44

If we apply the naive approach, the forecast for sales in April is directly tied to the actual sales achieved in March. This straightforward projection is what makes the naive method so quick to implement and understand.

Month	Actual Sales	Forecasted Sales
January	34	
February	37	
March	44	
April	?	44

Although the methodology is incredibly simple, its performance often works surprisingly well in practice, especially when historical data lacks strong seasonality or trend components. This tutorial provides a comprehensive, step-by-step example of how to perform naive forecasting using Microsoft Excel.

Setting Up the Data in Excel

The beauty of the naive method lies in its ease of implementation, especially using spreadsheet software like Microsoft **Excel**. We will now walk through the process using a 12-month sales history for an imaginary corporation. This detailed dataset allows us to demonstrate both the creation of the forecast and the subsequent calculation of accuracy metrics.

Begin by entering the historical sales data into two adjacent columns. Column A will contain the months, and Column B will house the corresponding actual sales figures. It is crucial to ensure the data is ordered sequentially by time period for accurate time-series analysis.

Below is the structure of the data input, covering a full year of observed values:

	A	B	C	D	E
1	**Month**	**Actual Sales**			
2	January	34			
3	February	37			
4	March	44			
5	April	47			
6	May	48			
7	June	48			
8	July	46			
9	August	43			
10	September	32			
11	October	27			
12	November	26			
13	December	24			
14					
15					
16					
17					
18					

Generating the Naive Forecasts

Once the actual data is entered, we can proceed to create the forecast column. Remember the core rule: the forecast for period 't' is equal to the actual value from period 't-1'. In Excel, this translates to a simple cell reference command.

For example, the forecast for February (Cell C3) must equal the actual sales from January (Cell B2). We cannot forecast January sales using this method because we lack data from the preceding period (December of the previous year). Therefore, the forecast column will always start one row below the actual data column.

The following illustration demonstrates how to apply this simple formula across all remaining months, producing a column of naive predictions:

	A	B	C	D	E
1	**Month**	**Actual Sales**	**Forecasted Sales**	Formula used	
2	January	34			
3	February	37	34	=B2	
4	March	44	37	=B3	
5	April	47	44	=B4	
6	May	48	47	=B5	
7	June	48	48	=B6	
8	July	46	48	=B7	
9	August	43	46	=B8	
10	September	32	43	=B9	
11	October	27	32	=B10	
12	November	26	27	=B11	
13	December	24	26	=B12	
14					
15					
16					
17					
18					

This output provides a baseline understanding of what future performance might look like if recent performance trends were to repeat exactly. This forecast will now be evaluated for accuracy.

Calculating Forecast Accuracy Metrics

A forecast is only useful if we understand how accurate it is. After generating the predictions, the next critical step is quantifying the error between the forecasted values and the actual observed values. This involves calculating several standard metrics used in forecasting analysis.

Two of the most widely used metrics for measuring forecast accuracy are:

Mean Absolute Percentage Error (MAPE)
Mean Absolute Deviation (MAD)

These metrics provide different perspectives on the magnitude of the forecasting error, allowing analysts to choose the most appropriate measure based on their specific business requirements. MAPE is scale-independent, while MAD retains the original units of measurement.

Determining Mean Absolute Percentage Error (MAPE)

The Mean Absolute Percentage Error (MAPE) is calculated by finding the absolute difference between the actual and forecasted values, dividing that by the actual value (to get a percentage error), and then averaging these percentage errors across all periods. This metric is expressed as a percentage and is excellent for comparing the accuracy of forecasts across different datasets or models.

The image below illustrates the necessary Excel calculations--specifically, calculating the absolute percentage error for each period and then summing them to find the overall MAPE value:

	A	B	C	D	E
1	**Month**	**Actual Sales**	**Forecasted Sales**	**Absolute Percent Error**	Formula used
2	January	34			
3	February	37	34	8.11	=ABS(B3-C3)/B3*100
4	March	44	37	15.91	=ABS(B4-C4)/B4*100
5	April	47	44	6.38	=ABS(B5-C5)/B5*100
6	May	48	47	2.08	=ABS(B6-C6)/B6*100
7	June	48	48	0.00	=ABS(B7-C7)/B7*100
8	July	46	48	4.35	=ABS(B8-C8)/B8*100
9	August	43	46	6.98	=ABS(B9-C9)/B9*100
10	September	32	43	34.38	=ABS(B10-C10)/B10*100
11	October	27	32	18.52	=ABS(B11-C11)/B11*100
12	November	26	27	3.85	=ABS(B12-C12)/B12*100
13	December	24	26	8.33	=ABS(B13-C13)/B13*100
14			**MAPE**	9.90	=AVERAGE(D3:D13)
15					
16					
17					
18					

In this specific example, the resulting MAPE is calculated to be **9.9%**. This indicates that, on average, the naive forecast deviated from the actual sales figures by approximately 9.9%.

Calculating Mean Absolute Deviation (MAD)

The Mean Absolute Deviation (MAD) measures the average magnitude of the errors without considering their direction. It is calculated by taking the absolute difference between the actual value and the forecasted value for each period, and then finding the average of those absolute differences. Unlike MAPE, MAD is expressed in the same units as the original data (e.g., dollars, units sold, etc.).

The subsequent illustration shows the required columns and formulas used within Excel to derive the MAD value:

	A	B	C	D	E
1	**Month**	**Actual Sales**	**Forecasted Sales**	**Absolute Deviation**	Formula Used
2	January	34			
3	February	37	34	3.00	=ABS(B3-C3)
4	March	44	37	7.00	=ABS(B4-C4)
5	April	47	44	3.00	=ABS(B5-C5)
6	May	48	47	1.00	=ABS(B6-C6)
7	June	48	48	0.00	=ABS(B7-C7)
8	July	46	48	2.00	=ABS(B8-C8)
9	August	43	46	3.00	=ABS(B9-C9)
10	September	32	43	11.00	=ABS(B10-C10)
11	October	27	32	5.00	=ABS(B11-C11)
12	November	26	27	1.00	=ABS(B12-C12)
13	December	24	26	2.00	=ABS(B13-C13)
14			**Mean Abs. Deviation**	3.45	=AVERAGE(D3:D13)
15					
16					
17					
18					
19					

For this dataset, the Mean Absolute Deviation is found to be **3.45**. This means the forecast was, on average, off by 3.45 units of the product sold.

Interpreting Results and Benchmarking

The primary purpose of implementing the naive forecasting model is to establish a **benchmark**. The accuracy metrics (MAPE of 9.9% and MAD of 3.45) are not meaningful in isolation. Their utility comes from comparison against alternative models.

To determine if this simple forecast is genuinely useful for operational planning, we must compare its accuracy measurements against those generated by more sophisticated forecasting models, such as Exponential Smoothing or ARIMA. If a more complex model only marginally improves accuracy, the naive method might be preferred due to its simplicity and lower implementation cost.

If, however, a more advanced technique yields significantly lower error rates, it justifies the complexity. The naive forecast, therefore, acts as a crucial first step in any robust time-series analysis, providing a clear, easily understandable starting point for evaluating future predictive efforts.