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Accuracy vs. Interpretability: Balancing Trade - Offs in Forecasting Models

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Abstract: ***As data scientists delve into the realm of forecasting models, a crucial consideration emerges - the delicate trade - off between accuracy and interpretability. This paper explores the intrinsic relationship between these two metrics, recognizing that heightened accuracy often begets decreased interpretability and vice versa. The discussion extends to the broader notion of accuracy, expressed as a percentage and evaluated through complementary metrics like accuracy and error rates. This section emphasizes the importance of accuracy in gauging the overall correctness of forecasting models, particularly applicable in classification scenarios. On the flip side, interpretability surfaces as a crucial facet in forecasting, denoting the ease with which humans can decipher a model's decision - making processes. The paper then navigates the strategies for balancing the accuracy - interpretability trade - off. Linear models and decision trees emerge as interpretable alternatives, while ensemble models and deep learning architecture promise heightened accuracy at the cost of interpretability. Exponential smoothing models present an intriguing middle ground, offering a balance between accuracy and interpretability in time series forecasting.***

Keywords: forecasting, interpretability, linear models, ensemble, regression, machine learning, deep learning

1. Introduction

As a data scientist, it is essential to understand the trade - offs between accuracy and interpretability in forecasting models. In general, the more accurate a model is, the less interpretable it becomes. This is because the most accurate models are often complex and difficult to understand. On the other hand, interpretable models are often less accurate.

Defining the Trade - off: Accuracy and Interpretability

Accuracy:
Accuracy and error are measures that evaluate the performance of a forecasting model by quantifying the difference between predicted values and actual observations. Let's define these terms:

Error in Forecasting [4]: Error in forecasting refers to the discrepancy between the predicted values generated by a forecasting model and the actual observed values. It provides insight into how well the model's predictions align with reality. Several types of errors are commonly used to assess forecasting performance [3]:

1) Mean Absolute Error (MAE): MAE=n1∑i=1n∣Yi−Y^i∣ AE represents the average absolute difference between actual (Y_i) and predicted ($\hat{Y}_i$) values.
2) Mean Squared Error (MSE): MSE=n1∑i=1n (Yi−Y^i) 2 MSE calculates the average squared difference between actual and predicted values. Squaring emphasizes larger errors.
3) Mean Absolute Percentage Error (MAPE): MAPE=n1∑i=1n (∣Yi∣∣Yi−Y^i∣) ×100% MAPE expresses the average percentage difference between actual and predicted values.

These error metrics help quantify the accuracy of a forecasting model by capturing the magnitude and direction of the discrepancies.

Accuracy in Forecasting:
Accuracy, in the context of forecasting, is a broader measure that gauges the overall correctness of a forecasting model's predictions. It is often expressed as a percentage and can be computed using various metrics, including:

$$\text{Accuracy}=1-\text{Error Rate}$$

Accuracy is the complement of the error rate, providing a measure of how often the model's predictions are correct. It is particularly useful for assessing classification models, where predictions are categorized as correct or incorrect.

Relationship Between Error and Accuracy:

Low Error (e. g., low MAE, MSE, RMSE, or MAPE):
Indicates smaller discrepancies between predicted and actual values.
Higher accuracy, as the model's predictions closely match observed values.

High Error (e. g., high MAE, MSE, RMSE, or MAPE):
Signifies larger discrepancies between predicted and actual values.
Lower accuracy, as the model's predictions deviate significantly from observed values.

Interpretability (I): Interpretability in forecasting refers to the ease with which humans can comprehend the model's decision - making process. While there is no precise mathematical formula for interpretability, it often correlates with the simplicity of the model structure and the transparency of its internal workings.

Balancing tradeoffs:
There are several ways to balance the trade - off between accuracy and interpretability. One way to balance the trade - off between accuracy and interpretability is to use a simple linear model. Linear models are easy to interpret and can be used to make accurate predictions. However, they may not be

suitable for all types of data. For example, if the data has a non - linear relationship, a linear model may not be able to capture this relationship.

Another way to balance the trade - off is to use a decision tree. Decision trees are easy to interpret and can be used to make accurate predictions. They work by splitting the data into smaller subsets based on a set of rules. However, decision trees can be prone to overfitting, which can lead to poor performance on new data.

An alternative way for moderate accuracy and high interpretability is to use Exponential smoothing models [1], strike a balance between accuracy and interpretability. Exponential smoothing is a time series forecasting method that uses a weighted average of past observations to make predictions. The basic equation for simple exponential smoothing is as follows:

$$y\hat{}t+1=\alpha yt+ (1-\alpha)\, y\hat{}t$$

Where
$y\hat{}t+1$ is the forecast for the next period.
yt is the observed value at time t.
$y\hat{}t$ is is the forecast for time t.
α is the smoothing parameter (also known as the smoothing factor) with $0\leq\alpha\leq1$.

This equation represents a weighted average, where the forecast (y^t+1) is a combination of the observed value at the current time (yt) and the previous forecast ($y\hat{}t$). The smoothing parameter α determines the weight assigned to the current observation versus the past forecast. A higher α gives more weight to the current observation, making the model more responsive to recent changes.

The initial forecast ($y\hat{}1$) is typically set equal to the first observed value (y1).

Exponential smoothing [1] can be extended to handle trends and seasonality, leading to models like Holt's method and Holt - Winters method. The equations for these extended models include additional components to capture trend and seasonality effects.

A third way to balance the trade - off is to use an ensemble model. Ensemble models, such as Random Forests, offer a compromise between accuracy and interpretability. By aggregating predictions from multiple simpler models (decision trees), Random Forests can achieve high accuracy while still providing insights into feature importance and decision processes.

Ensemble models combine the predictions of multiple models to make a final prediction. This can lead to more accurate predictions than using a single model. However, ensemble models can be difficult to interpret.

Deep learning models [5] are becoming popular in the field of forecasting. Deep learning models are characterized by intricate architectures, can achieve remarkable accuracy in forecasting tasks. However, the complex interconnections of nodes and weights make these models less interpretable. Understanding the reasoning behind a specific prediction becomes challenging, and these models might be viewed as "black boxes. " Different types of deep learning models used for forecasting are shown in Figure 1.

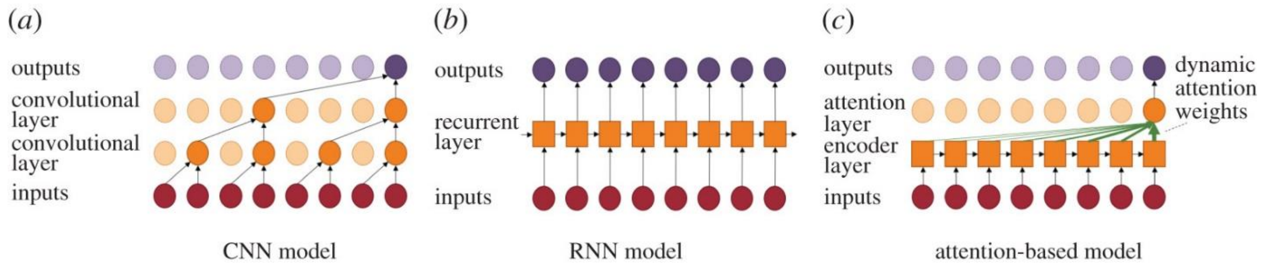

Figure 1: Incorporating temporal information using different encoder architectures. (a) CNN model, (b) RNN model and (c) attention - based model. [5]

In general, the choice between accuracy and interpretability depends on the specific problem at hand. If the goal is to make accurate predictions, then a more complex model may be necessary. However, if the goal is to understand the relationship between the variables, then a simpler model may be more appropriate.

The following equation shows the trade - off between accuracy and interpretability:

$$Accuracy = f\,(Interpretability)$$

Where f is a function that maps interpretability to accuracy. The goal is to find the optimal balance between accuracy and interpretability.

Real - world Applications and Considerations

1) Financial Forecasting:
Scenario: High Accuracy, Low Interpretability

In financial forecasting, accuracy is crucial for making informed investment decisions. Complex models may accurately predict stock prices, but the lack of interpretability could pose challenges in explaining decisions.

2) Demand Forecasting:
Scenario: Moderate Accuracy, High Interpretability

In demand forecasting, interpretability is vital for supply chain decisions. Models that maintain interpretability can help understand the factors influencing demand, striking a balance between accuracy and transparency.

Things continue to evolve in all industries, higher accuracy and higher interpretability is expected across all industries. Communication is key for data scientists to ensure they communicate the tradeoffs between models that provide high accuracy vs. interpretability.

2. Conclusion

In conclusion, balancing the trade - off between accuracy and interpretability is an important consideration when building forecasting models. There are several ways to balance the trade - off, including using a simple linear model, a decision tree, or an ensemble model. The choice between accuracy and interpretability depends on the specific problem at hand. By understanding the trade - offs between accuracy and interpretability, data scientists can build models that are both accurate and interpretable.

Real - world applications illustrate the scenarios where accuracy takes precedence, such as in financial forecasting for investment decisions, and where interpretability is paramount, as seen in demand forecasting influencing supply chain decisions. The evolving landscape of industries demands both higher accuracy and interpretability, urging effective communication from data scientists to articulate the trade - offs inherent in their models.

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