Evaluation Metric

Evaluation metrics are benchmarks used to quantify the performance of a machine learning model. They help measure how well the model is performing on a given dataset. These metrics are crucial because they provide a quantifiable assessment of the model's predictive power and can guide model selection, hyperparameter tuning, and overall improvement strategies. Here's why they're important:

**1. Quantitative Assessment**

**2. Model Selection**

**3. Hyperparameter Tuning**

**4. Detecting Overfitting or Underfitting**

**5. Communicating Model Performance**

Mean Squared Error (MSE) is a commonly used evaluation metric in time series forecasting, providing insights into the performance of predictive models. In the context of time series forecasting, MSE quantifies the average squared difference between the predicted values and the actual values over a specific time horizon.

Here's why we used MSE as an Evaluation Metric for our time series forecasting:

1. **Error Measurement: MSE calculates the average of the squared differences between predicted and actual values across the entire forecast horizon.**
2. **Interpretability: MSE is in squared units of the target variable, making it interpretable within the context of the problem domain.**
3. **Model Comparison: MSE allows for direct comparison between different forecasting models. Lower MSE values indicate better performance in terms of minimizing prediction errors.**

MSE Scores for the models:

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**Observations:**

1. **Holt-Winters Outperforms Others:**
   * Holt-Winters has the lowest MSE among all the models, indicating that, based on this metric alone, it performs the best in terms of minimizing prediction errors for the specific dataset or task.
2. **Traditional Models vs. Deep Learning Models:**
   * The MSE scores of Holt-Winters and ARIMA (traditional models) are notably lower than those of Bi LSTM, CNN, and SVR (deep learning models) for this particular dataset.
   * In this scenario, traditional statistical models like Holt-Winters and ARIMA seem to perform better than deep learning models.
3. **Performance Ranking:**
   * Following Holt-Winters, ARIMA has the next lowest MSE, indicating relatively good performance.
   * Bi LSTM, CNN, and SVR have higher MSE values, suggesting they might not be as effective in minimizing prediction errors compared to the traditional models in this specific context.
4. **Consideration of Other Factors:**
   * MSE is just one metric; other factors like computational complexity, interpretability, and scalability should also be considered when selecting the appropriate model for deployment.

**Interpretation:**

* **Holt-Winters appears to be the most accurate model** among those listed based on MSE. However, further analysis is needed to understand why traditional models outperformed deep learning models for this dataset. It might be due to the dataset characteristics, model tuning, or the nature of the time series itself.
* **It's essential to not rely solely on MSE:** While it's a useful metric, considering the overall performance, suitability for the problem, and domain-specific requirements is crucial for model selection.
* **Model selection depends on various factors:** While Holt-Winters might have the lowest MSE, other models might have advantages in different scenarios (e.g., deep learning models for capturing complex nonlinear relationships).

Understanding these MSE scores offers a comparative view, but it's crucial to consider these results within the context of the specific dataset, the business problem, computational requirements, and the trade-offs between model complexity and interpretability.

**References**:

* **"A Comparative Study of ARIMA and ANN Models Used for Financial Time Series Forecasting" by Hasan, M.K., and Al-Emran, A.M. (2016)**
* **"Forecasting Crude Oil Price Using Artificial Neural Networks" by Zhang, S., and Qi, Y. (2005):**
* **“Crude Oil Price Forecasting Using ARIMA and GARCH Models"**
* **“Crude Oil Price Forecasting Using LSTM Neural Networks"**
* "Crude oil price analysis and forecasting: A perspective of the 'new triangle'"