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Time Series Methods in Meteorology: A Review of Predictive Models and Applications

Atharva Naik[1, *], Ninad Mungekar[1], Surabhi Pandit[1], Parth Vyavahare[1], Suresh Mestry[2]

Abstract

The accurate prediction of time series data holds substantial significance in various fields, enabling informed decision-making and resource optimization. In this study, temperature variations over time are predicted using the Autoregressive Integrated Moving Average (ARIMA) model. Reliable temperature projections are more important now than ever because of climate change and its effects. For time series prediction problems, the ARIMA model—which is well-known for its ability to capture temporal dependencies in data—can be applied. It is possible to apply and adjust this model to take into account the unique features of temperature data, like trends and seasonality. To ensure quality and consistency, historical temperature data is gathered and pre-processed. Using machine learning algorithms, the suggested works forecast the weather based on variables like temperature, wind, and humidity. The weather prediction industry has had success with computer-aided prediction systems that use machine learning models. The experiment emphasises the value of applying cutting-edge data analysis methods to practical problems and shows how larger prediction systems may be refined even further.

Keywords: Weather Forecasting, ARIMA, Time Series data.

INTRODUCTION

In today's dynamic world, accurate weather forecasting is crucial for numerous sectors, including agriculture, transportation, energy management, and disaster preparedness. The ability to predict temperature variations over time is especially vital given the escalating concerns surrounding climate change and its potential ramifications. The main goal of this project is to forecast temperature changes by developing and implementing the Autoregressive Integrated Moving Average (ARIMA) model. This will help make decisions more intelligent and enable preventative actions against climate change. It is impossible to exaggerate the importance of time series analysis, especially in weather forecasting. Time series data, characterized by its sequential nature and temporal dependencies, necessitates specialized models capable of capturing underlying patterns and trends.

***Author for Correspondence**
Atharva Naik
E-mail: atharvanaik13@gmail.com

[1]Student, Department of Computer Engineering, Rajiv Gandhi Institute of Technology (affiliated to the University of Mumbai), Mumbai, Maharashtra, India.
[2]Assistant Professor, Department of Computer Engineering, Rajiv Gandhi Institute of Technology (affiliated to the University of Mumbai), Mumbai, Maharashtra, India.

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The ARIMA model, renowned for its effectiveness in modelling time-dependent data, offers a robust framework for temperature prediction tasks. By leveraging historical temperature data, this project endeavors to construct a reliable forecasting framework adept at anticipating temperature fluctuations with precision.

The primary objective of this endeavor is to address the pressing need for accurate temperature forecasts amid the backdrop of climate variability and change. Through the utilization of advanced data analysis techniques and modelling methodologies, the project seeks to enhance our understanding of temperature dynamics and improve predictive capabilities. By elucidating the intricacies of temperature variation and seasonality, the ARIMA model serves as a valuable tool for stakeholders across diverse domains, empowering them to make informed decisions and adapt to evolving climatic conditions.

This report delves into the methodology and implementation of the ARIMA model for weather forecasting, emphasizing the iterative process of data collection, pre-processing, model construction, and validation. Furthermore, it explores strategies to optimize the model's accuracy and reliability, including parameter tuning and model evaluation techniques. By employing industry-standard programming languages and libraries tailored for time series analysis, the project exemplifies the practical application of computational tools in addressing real-world challenges. In the end, this initiative emphasises how critical it is to use data-driven strategies to lessen the effects of climate change and promote environmental resilience.

Through continuous refinement and integration with broader predictive systems, the ARIMA-based weather forecasting framework offers a pathway towards more effective risk management strategies and sustainable decision-making practices in a rapidly changing world.

RELATED WORK

Research and innovation in this field have been made to meet the challenges of an increasingly complex and dynamic climate system. In this literature review, we explored the key findings and advancements in time series weather prediction based on previous research papers, emphasizing the evolution of techniques, data sources, and challenges in this field.

The ability of many conventional weather forecasting models to produce forecasts with high spatial and temporal resolution is limited. This means that they may not capture fine-scale weather patterns or rapid changes in weather conditions, which can be particularly important for local and short-term forecasts. Short-term weather forecasts (e.g., up to 48 hours) can be challenging due to the inherent complexity of atmospheric processes. Traditional weather forecasting systems are not well-suited for addressing long-term climate change patterns. Climate models differ from weather models and require different approaches and data. Consequently, existing weather forecasting systems may not adequately inform climate adaptation strategies.

[1] used historical data from Pune, Maharashtra, to develop a SARIMA (Seasonal Autoregressive Integrated Moving Average) model for temperature prediction. For observation, the historical dataset spanning from 2009 to 2020 has been used. Using the seasonal autoregressive integrated moving average (SARIMA) model is another widely used technique when a time series has a repeating cycle, as opposed to manually breaking it down to match an ARIMA model. The growing popularity of time series is partly due to the decreasing processing power and cost of hardware. The future year's plan can be established using the approach. The autocorrelation function, partial autocorrelation function, and standardised residuals were used to assess the model's goodness of fit.

We find that SARIMA (1,1,1)(1,1,1)12 is capable of excellent performance representation. For the SARIMA model, [2] we found an RMSE of 0.76233 and an MAE of 0.60850. The diagnostics of the model indicated that it performed well in temperature prediction.

This article makes a similar contribution by simulating two crucial weather parameters—the maximum and minimum temperatures—using artificial neural networks (ANNs) in MATLAB. The model to forecast maximum and minimum temperature has been tested over 40 years and trained using the last 60 years of real data collected from 1901 to 1960. The model, based on a multilayer perceptron, has the potential to be successfully used to weather forecasting, as confirmed by the mean square error function (MSE) results.

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An analysis of statistical and neuro-fuzzy network models for İstanbul, Turkey weather forecasting is presented in this research.[3] Nine years of data (2000–2008) on daily average temperature (dry/wet), air pressure, and wind speed were utilised to create the models. Auto Regressive Moving Average (ARIMA) and Adaptive Network Based Fuzzy Inference System (ANFIS) models have been used.

Existing systems may not always provide the necessary integration and customization to cater to the specific needs of these sectors, potentially hindering their efficiency and effectiveness. Addressing these limitations often requires ongoing research and advancements in weather forecasting models, data assimilation techniques, and the development of user-friendly interfaces. Additionally, a multidisciplinary approach that involves meteorologists, computer scientists, and stakeholders from various sectors is essential to overcome these challenges and improve.

A model is designed to process the time-series data and accordingly predict the appropriate weather conditions. It also covers important aspects such as data collection, model validation, and ethical considerations. Time series prediction of temperature has gained popularity due to the declining cost and increased capability of hardware. The use of time series models allows us to analyse historic temperature data and develop suitable models for future prediction. The creation of an ARIMA model for temperature prediction is the aim of this work. By analysing the historic temperature data from 1996 to 2017, we aim to accurately forecast future temperature values. As we progress through this project, we are excited to share our findings and developments in the realm of time series-based weather prediction using the ARIMA model. This project will contribute to a more resilient and well-informed society, better equipped to adapt to the challenges posed by the world's dynamic climate.

ANALYSIS/FRAMEWORK/ALGORITHM

A data science framework, ARIMA model is implemented in this proposed system. Among the many applications of the powerful time series forecasting model ARIMA (Auto Regressive Integrated Moving Average) is weather prediction. ARIMA models are the most well-known models for time series forecasting. Box and Jenkins were the ones who first brought it up (1970). (p,d,q) is the general ARIMA model, where p denotes the autoregressive parameters, d the number of differencing operators, and q the moving average parameter. According to Box and Jenkins, the general stochastic models are ARIMA Models are specified by three order parameters: (p, d, q), were,

1. *AR(p) auto regression*: This regression model leverages the interdependence between the current observation and past observations spanning a previous period. An autoregressive component, denoted as AR(p), involves incorporating previous values into the regression equation for the time series.
2. *I(d) integration:* Integration involves differencing observations, which means subtracting the current observation from the one at the previous time step. This process is applied iteratively d times to achieve stationarity in the time series data.
3. *MA(q) moving average:* The link between an observation and the residual error that arises from using a moving average model on earlier observations is what drives the moving average model. The model's error is described by the moving average component as a mixture of previous error terms. The number of terms to include in the model is indicated by the order, q.

The Use of Time Series Information The basis of weather forecasting is time series data, which is defined as observations that are gathered over an extended period of time at regular intervals. Numerous variables are covered by these statistics, including temperature, humidity, wind speed, and precipitation. By analyzing these time series data, we can uncover patterns, trends, and dependencies that are invaluable for predictive modelling. Time series is a set of observations on the values that a variable takes at different times. Time series are used in econometrics, statistics, mathematical finance earthquake prediction and weather forecasting. Time series forecasting for weather data is a challenging task due to the complex and dynamic nature of weather patterns.

Steps for Applying ARIMA Model

1. Data collection
2. Data preprocessing
3. Model selection
4. Model training
5. Model validation
6. Forecasting
7. Evaluation
8. Fine-tuning

1. *Data collection:* Compile time series data from the past that is pertinent to your issue. This might be anything from sales numbers to temperature readings to stock prices. Ensure the data is consistent, reliable, and covers a sufficient time span for meaningful analysis.
2. *Data preprocessing:*
   i. *Manage missing values:* Depending on the situation, either impute or eliminate them.
   ii. *Look for anomalies:* Determine which extremes could have an impact on the model's performance.
   iii. *Resample as necessary:* Data should be converted to a regular frequency (e.g., daily to monthly).
   iv. *Stationarity:* Stationarity is assumed by ARIMA. To make your data steady, transform it using techniques like differencing.
3. *Model choice:* Moving Average (MA), Integrated (I), and Auto-Regressive (AR) are the three parts of ARIMA. By verifying stationarity, ascertain the differencing order (I). Identify the AR and MA orders using ACF (Auto-Correlation Function) and PACF (Partial Auto-Correlation Function) plots. Consider seasonal components (SARIMA) if your data exhibits seasonality.
4. *Model training:* Divide your dataset into sets for training and validation. Using the selected orders, fit the ARIMA model to the training set. Optimise hyperparameters (p, d, and q) by employing methods such as Bayesian optimisation or grid search.
5. Validate the model by assessing its output on the validation set. Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) are examples of common metrics.
6. *Forecasting:* Use the model to project future values once you're comfortable with it. Produce projections for the intended time frame.
7. *Evaluation:* Make a comparison between the predicted and observed values. Evaluate the precision and dependability of your forecasts. Put the results into visual form with graphs and charts.
8. *Fine-tuning:* Adjust your model in response to evaluation feedback.

Adjust hyperparameters, retrain, and validate iteratively. Consider incorporating exogenous variables if available (e.g., economic indicators, holidays).

DESIGN DETAIL

The dataset comprises various parameters, including date-time, temperature, humidity, moonrise, wind speed, wind direction, and pressure. To ensure data quality features with a significant amount of missing data were excluded, with temperature chosen as the input parameter. The process of temperature prediction comprises of following steps:

- *Data collection:*
  - Compile historical weather information from dependable sources. This should include relevant parameters like temperature, humidity, wind speed, precipitation, etc., along with their corresponding timestamps.
- *Differencing the series to achieve stationarity*
  - Use differencing to make the data stationary if it is not (i.e., if its mean or variance changes over time). This involves subtracting each data point from its previous point.

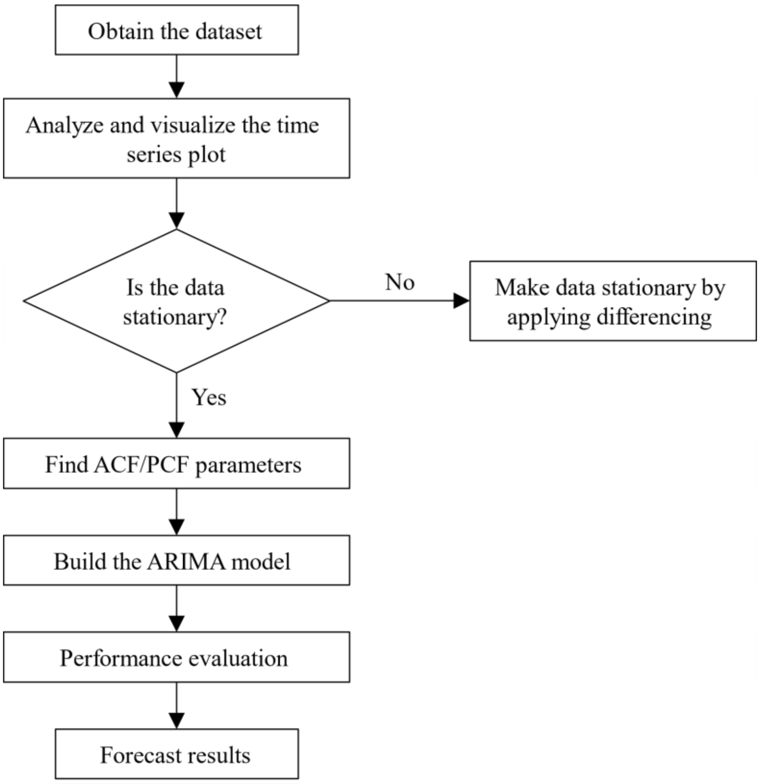

Figure 1. Flowchart of the proposed system.

- *Identify the model*
  - Based on the ACF and PACF plots and any differencing applied, determine the appropriate ARIMA model order (p, d, q).
- *Learning the model*
  - Train the ARIMA model on the historical weather data. Using time series analysis, autocorrelation, and partial autocorrelation plots, the orders of differencing (d), autoregressive order (p), and moving average order (q) are determined. Estimate the Model Parameters:
  - Determine the ARIMA model's parameters (coefficients) using statistical techniques. This involves techniques like maximum likelihood estimation.
- *Diagnostic checking: is the model accurate?*
  - Evaluate the model's performance and assumptions. Check for normality of residuals, absence of autocorrelation in residuals, and white noise properties. Use statistical tests and visualizations.
- *Use the model for forecasting*
  - Future weather forecasts can be created using the ARIMA model once it has been trained and verified. Provide new data points to the model and generate predictions for upcoming time periods.
- *Forecasting model explanation*
  - Communicate the results of your forecasting model. Explain how the ARIMA model works, including concepts like autoregressive components (AR), differencing (I), and moving average components (MA). Describe how these elements combine to make accurate forecasts based on historical patterns.
- *Error forecast*
  - The residuals, or the variations between the observed and anticipated values, can be examined after the ARIMA model has been fitted. This can assist in finding any biases or patterns in the model's mistakes.

DETAILED DESIGN

An appropriate time series data of sufficiently large timeline is selected. Following this selection, a time series plot was generated using a data visualization technique. However, the initial time series data was found to be non-stationary. Differentiating was used to make it stationary in order to remedy this. It is crucial not to over-difference the series, as excessive differencing can lead to an ostensibly stationary series, thereby affecting the model parameters. Determining the appropriate order of differencing is paramount. The right order of differencing signifies the minimal differencing required to render the series nearly stationary, characterized by fluctuations around a predefined mean and a rapid decrease of autocorrelation in the ACF plot. To embark on this determination, the first step involves assessing the stationarity of the series by employing the Augmented Dickey Fuller test (ADF Test) available in the stats models package. This step is necessary because differencing is only needed when the series is non-stationary. In cases where the series is already stationary, no further differencing (i.e., d=0) is warranted. In the ADF test, the null hypothesis (Ho) asserts that the time series is non-stationary.

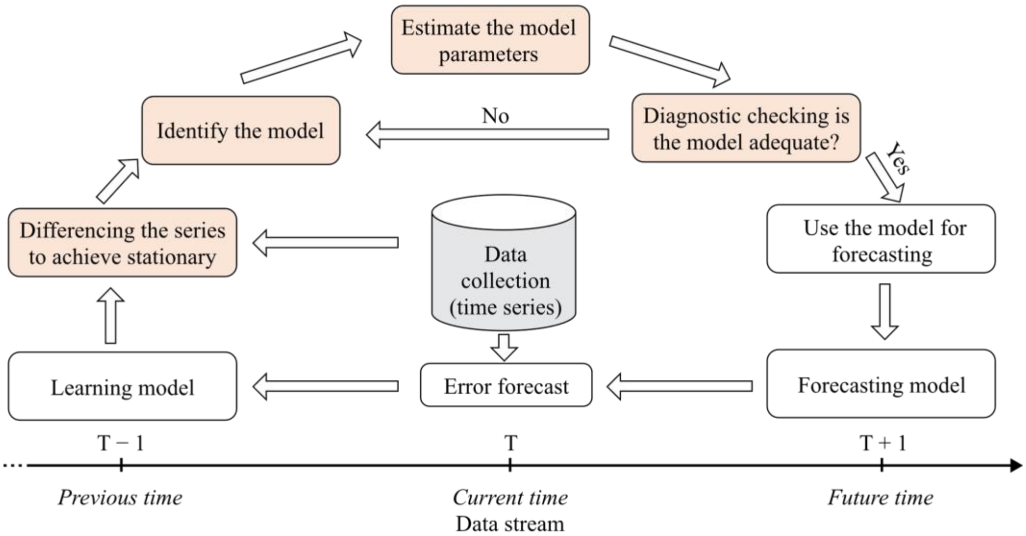

Figure 2. System architecture of prediction model.

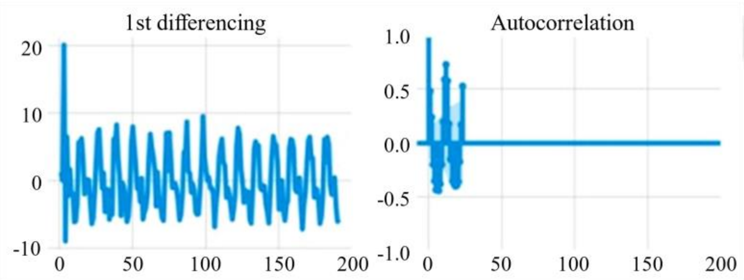

Figure 3. ACF plot of 1st differenced series.

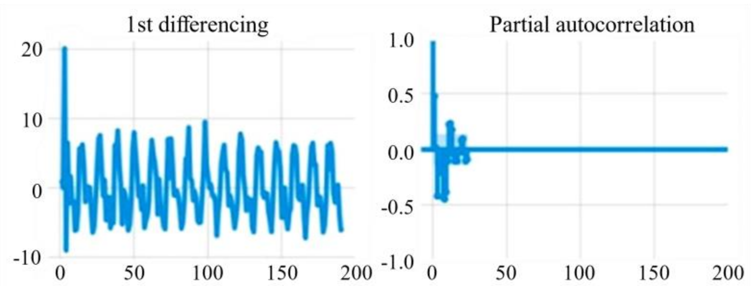

Figure 4. PACF plot of 1st differenced series.

The Augmented Dickey-Fuller test was employed to assess stationarity, aiming for a p-value less than or equal to 0.05 ($P \leq 0.05$). The order of differencing, denoted as 'd', was selected to minimize the standard deviation. Once differencing was applied, the resulting stationary time series might still exhibit autocorrelated patterns. To address this, autoregressive (AR) and moving average (MA) terms were introduced into the forecasting model, with $p \geq 1$ and $q \geq 1$, respectively. To identify suitable values for p and q, autocorrelation functions (ACF) and partial autocorrelation functions (PACF) were plotted.

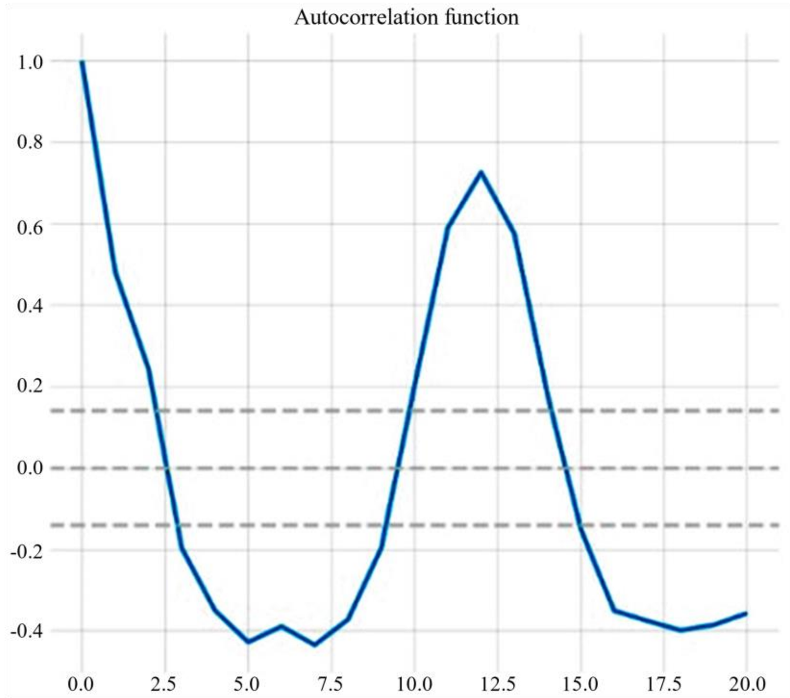

Figure 5. Auto correlation function.

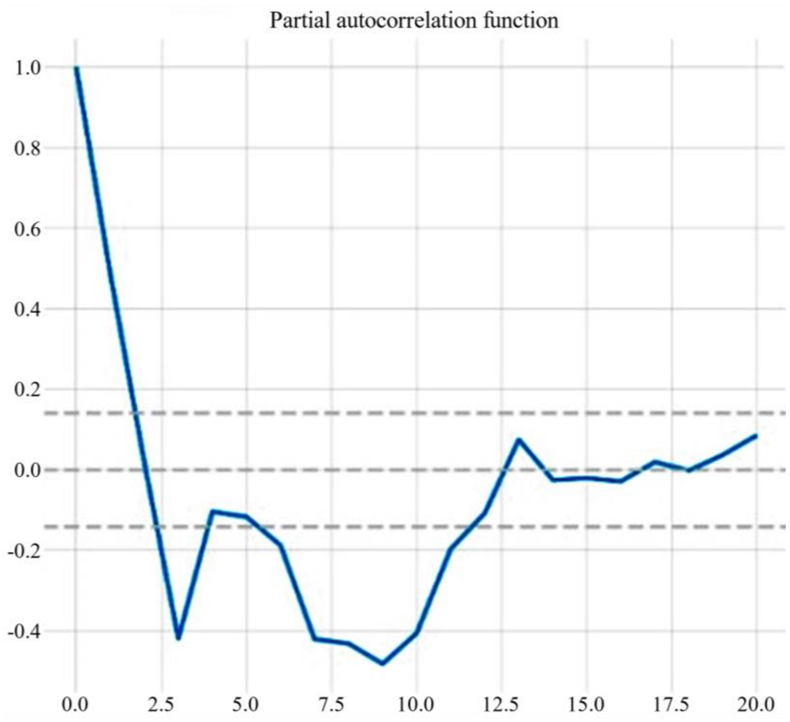

Figure 6. Partial autocorrelation function.

Once we've identified the ARIMA model (p, d, q), we need to estimate the model parameters. This involves using an algorithm to find the optimal values for the parameters. Finally, an ARIMA (AutoRegressive Integrated Moving Average) model was constructed using the preprocessed data. ARIMA models encompass autoregressive (AR) and moving average (MA) components, which collectively help in forecasting time series data. The constraints can be defined as

- p: the number of interval observations in the model; also known as the interval order.
- d: differencing is needed to make the series stationary.
- q: the size of the moving average window; also known as the order of the moving average.

Performance evaluation of an ARIMA (AutoRegressive Integrated Moving Average) model is crucial to determine how well the model fits the time series data and how accurately it makes forecasts.

After estimating the model, it's essential to assess its adequacy and fit to the data. Key considerations include Residual analysis. It examines the residuals (differences between observed and predicted values) for patterns, autocorrelation, and normality. Performance evaluation of an ARIMA (Auto Regressive Integrated Moving Average) model is crucial to determine how well the model fits the time series data and how accurately it makes forecasts. After evaluating the performance of an ARIMA (Auto Regressive Integrated Moving Average) model, you can use the model to make predictions for future weather conditions

METHODOLOGY

ARIMA models are the most well-known of models for time series forecasting. Box and Jenkins were the ones who first brought it up (1970). (p,d,q) is the general ARIMA model, where p denotes the autoregressive parameters, d the number of differencing operators, and q the moving average parameter. According to Box and Jenkins, the general stochastic models are

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3. *MA(q) moving average:* The moving average model relies on the relationship between an observation and the residual error resulting from a moving average model applied to past observations. The moving average component characterizes the model's error as a combination of past error terms. The order, denoted as q, specifies the number of terms to include in the model.

Order of Differencing (d)

As previously mentioned, differencing is employed to achieve stationarity in a time series. However, it's crucial not to over-difference the series, as excessive differencing can lead to an ostensibly stationary series, thereby affecting the model parameters.

Determining the appropriate order of differencing is paramount. The right order of differencing signifies the minimal differencing required to render the series nearly stationary, characterized by fluctuations around a predefined mean and a rapid decrease of autocorrelation in the ACF plot.

To embark on this determination, the first step involves assessing the stationarity of the series by employing the Augmented Dickey Fuller test (ADF Test) available in the stats model’s package. This step is necessary because differencing is only needed when the series is non-stationary. In cases where the series is already stationary, no further differencing (i.e., d=0) is warranted.

The null hypothesis (Ho) in the ADF test posits that the time series is non-stationary. Consequently, if the p-value obtained from the test falls below the significance level of 0.05, we reject the null hypothesis and conclude that the time series is indeed stationary.

Hence, in our context, when the P-value exceeds 0.05, we proceed with determining the appropriate order of differencing.

Performance evaluation of ARIMA model is done by using several methods like
1. Mean absolute error (MAE)
2. Mean squared error (MSE)
3. Root mean squared error (RMSE)
4. Mean absolute percentage error (MAPE)
5. Cross-validation

1. *Mean absolute error (MAE):* MAE measures the average absolute difference between the actual and predicted values. It gives equal weight to all errors, regardless of their magnitude and direction.
2. *Mean squared error (MSE):* MSE measures the average squared difference between the actual and predicted values. It penalizes larger errors more heavily than smaller errors.
3. *Root means squared error (RMSE):* RMSE is the square root of the MSE and represents the average magnitude of the error. It is in the same unit as the original data, making it easier to interpret.
4. *Mean absolute percentage error (MAPE):* MAPE measures the average percentage difference between the actual and predicted values. It provides a relative measure of accuracy, making it useful for comparing models across different data sets.
5. *Cross-validation:* Cross-validation is a technique used to assess the performance of a model by splitting the dataset into training and testing sets. It helps to evaluate the model's ability to generalize to new data by simulating the process of model training and testing on multiple subsets of the data. Common methods include k-fold cross-validation and leave-one-out cross-validation.

After performance evaluation, we can use the model to make predictions for future time points. The steps to make predictions with an ARIMA model are as follows:
1. Select the Forecast Horizon
2. Re-fit ARIMA Model
3. Generate Forecasts
4. Prediction Intervals
5. Plot Predictions
6. Evaluate Predictions
7. Update and refine

1. *Select the forecast horizon:* The forecast horizon is the time period into the future for which predictions are desired. It is essential to determine the forecast horizon before proceeding with model fitting and prediction generation. The forecast horizon may vary depending on the specific application and business requirements.
2. *Re-fit ARIMA model:* Before generating forecasts, it's crucial to re-fit the ARIMA model using the entire dataset (including the training and validation data). Re-fitting the model ensures that it captures any changes or trends in the data that may have occurred since the initial model fitting. The model parameters, such as the autoregressive (AR) and moving average (MA) orders, may be re-estimated based on the updated dataset.
3. *Generate forecasts:* Once the ARIMA model is re-fitted, forecasts can be generated for the selected forecast horizon. Forecasts are typically generated by applying the fitted ARIMA model to future time periods beyond the end of the observed data. The forecast values represent the model's best estimate of future observations based on the historical data and the model's assumptions.

4. *Prediction intervals:* Prediction intervals provide a range of values within which future observations are expected to fall with a certain level of confidence. Prediction intervals quantify the uncertainty associated with the forecasts and account for potential errors or variability in future observations. Prediction intervals are often calculated based on the model's residuals and assumptions about the distribution of forecast errors.
5. *Plot predictions:* Visualizing the forecasted values alongside the observed data helps assess the model's performance and identify any discrepancies or patterns. Plotting predictions allows for visual inspection of trends, seasonality, and any deviations from the observed data. Graphical representation of forecasts facilitates communication and interpretation of the model results to stakeholders and decision-makers.
6. *Evaluate predictions:* Evaluation of predictions involves comparing the forecasted values to the actual observed data. Common evaluation metrics include Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). Evaluation metrics provide quantitative measures of the model's accuracy, precision, and reliability in predicting future observations.
7. *Update and refine:* After evaluating the predictions, it may be necessary to update and refine the ARIMA model based on the insights gained. This could involve adjusting model parameters, refining forecasting methods, incorporating additional data sources, or exploring alternative modeling techniques. Iterative refinement of the model helps improve its predictive performance and ensures that it remains robust and relevant over time.

PERFORMANCE EVALUATION

Accuracy

Assessing how well the ARIMA model's forecasts compare to other models: This involves comparing the accuracy of the ARIMA model's forecasts with those generated by alternative models or forecasting methods. Use standard accuracy metrics for comparison, such as Theil's U statistic, Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and so on. *Interpretation:* Accuracy is indicated by lower values of these measures, however it's crucial to take the demands of the forecasting assignment and its particular environment into account.

Effectiveness

The disparities between the observed and predicted values are known as residuals, and they are found while looking for patterns and autocorrelation in the model residuals. *Evaluation:* Random residuals with no autocorrelation or observable patterns are indicative of efficient models. *Techniques for analysis:* To look for autocorrelation or patterns in residuals, use statistical tests like the Durbin-Watson or Ljung-Box tests. Significant patterns or autocorrelation in residuals may suggest that the model is not adequately capturing all the information in the data, necessitating further investigation or model refinement.

Visual Inspection

Plotting observed and predicted values over time: Visualize how well the ARIMA model captures the patterns in the data. *Visualization techniques:* Plot original time series data alongside the model's fitted values and forecasted values. *Interpretation:* Assess whether the model captures trends, seasonality, or irregularities in the data accurately. Look for discrepancies or deviations between observed and predicted values.

Calibration and Verification

Testing the ARIMA model's performance: Validate the model's performance on separate validation datasets.b*Methods for validation*: Employ techniques such as holdout validation, cross-validation, or time series splitting to partition data into training and validation sets. *Assessment:* Compare the model's forecasts with actual observed values in the validation dataset to evaluate its accuracy, reliability, and generalization capabilities.

Forecast Lead Time Analysis

Evaluating performance at different time horizons: Assess how well the ARIMA model performs for various forecast lead times (e.g., short-term vs. long-term predictions). *Methods for evaluation*: Analyze accuracy metrics, residuals, and visualizations across different forecast horizons. *Interpretation:* Understand the strengths and limitations of the model at different lead times and tailor forecasts accordingly based on the application requirements. By considering these aspects in detail, analysts can comprehensively evaluate the performance of ARIMA models and make informed decisions regarding their suitability for forecasting tasks in diverse domains and scenarios.

CONCLUSION

In conclusion, the implementation of the ARIMA model for time-based weather forecasting presents a promising avenue for addressing the challenges associated with accurate temperature predictions. The evaluation and optimization strategies discussed ensure the model's reliability, while its real-world applications span various sectors, from agriculture to urban planning. Collaborations between meteorologists, data scientists, and stakeholders from diverse sectors can facilitate the development of more comprehensive and tailored weather forecasting systems. The ARIMA model stands as a cornerstone in the realm of time-based weather forecasting, offering a robust framework for harnessing historical data to predict future weather conditions. As we continue to refine and expand upon this methodology, we unlock new opportunities to safeguard lives, livelihoods, and the environment against the unpredictable forces of nature.

As we move towards a more interconnected and data- driven world, the integration of machine learning algorithms and artificial intelligence techniques with ARIMA modeling holds promise for enhancing the precision and reliability of weather forecasts. These developments open the door to customised solutions that address the unique requirements and preferences of individual users. As technology and data processing capabilities continue to expand, there are exciting potential for the development of weather prediction models. Interdisciplinary research and innovation in weather forecast methodologies can be fostered by cooperative efforts amongst government, industry, and academic institutions. By pooling expertise and resources, we can address complex challenges such as extreme weather events and climate change impacts with greater efficacy

Declaration of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript.

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