J. Electrical Systems 20-6s (2024): 2166-2177

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Forecasting Student Employment Trends in Colleges and Universities Education Using Time Series Analysis Algorithms

Abstract: - Student employment trends in colleges have been evolving, with a notable shift towards internships, co-op programs, and other experiential learning opportunities. Colleges are increasingly emphasizing the importance of gaining practical work experience alongside academic studies to enhance students' employability. This trend reflects the growing demand from employers for graduates who possess not only theoretical knowledge but also relevant skills and hands-on experience. This study investigates student employment trends within Colleges and Universities education through the application of time series analysis algorithms. Utilizing historical data spanning five years from 2019 to 2023, the study examines the dynamics of student employment rates and explores the effectiveness of forecasting methodologies, including ARIMA and Ranking with ARIMA (R-ARIMA). The findings reveal a consistent upward trend in student employment rates over the study period, indicating a favorable environment for student career opportunities within higher education institutions. Moreover, the accuracy of forecasting models is demonstrated through the close alignment between predicted and observed employment rates. Optimal ARIMA configurations are identified, providing insights for strategic planning and resource allocation to support student career development and success. The findings reveal a consistent upward trend in student employment rates over the study period, with the percentage of employed students increasing annually. For instance, the student employment rate rises from 65% in 2019 to 77% in 2023. This indicates a favourable environment for student career opportunities within higher education institutions. Moreover, the accuracy of forecasting models is demonstrated through the close alignment between predicted and observed employment rates. Optimal ARIMA configurations are identified, with the best-performing model achieving an AIC score of 95.3 and a BIC score of 99.8. These configurations provide insights for strategic planning and resource allocation to support student career development and success.

Keywords: Student Employment, Forecasting, Time Series Analysis, ARIMA, Ranking, Universities

1. Introduction

In recent years, student employment trends within Colleges and Universities education have showcased a notable evolution [1]. With the rising costs of education, students increasingly seek employment opportunities to alleviate financial burdens and gain practical experience simultaneously [2]. Part-time jobs on campus, such as tutoring, administrative roles, or research assistantships, remain popular choices due to their flexibility and alignment with academic schedules[3]. Moreover, internships and co-op programs continue to gain prominence as students recognize the importance of gaining industry-specific skills and networking early in their academic journeys [4]. Additionally, the digital age has ushered in remote work opportunities, expanding the horizons for students to engage in employment regardless of geographical constraints. As the landscape of work evolves, Colleges and Universities are adapting by offering career development services and integrating experiential learning opportunities into their curricula to better prepare students for the competitive job market [5]. Forecasting student employment trends in Colleges and Universities education using time series analysis algorithms involves a multifaceted approach that leverages historical data and predictive modeling techniques [6]. Time series analysis algorithms, such as ARIMA (AutoRegressive Integrated Moving Average) and exponential smoothing methods, enable researchers and administrators to identify patterns, seasonality, and trends in student employment data over time [7]. By analyzing factors like enrollment numbers, economic indicators, and job market dynamics, these algorithms can generate forecasts to anticipate future student employment trends [8]. Moreover, advanced machine learning techniques, including LSTM (Long Short-Term Memory) networks and Prophet models, offer enhanced capabilities for capturing complex patterns and nonlinear relationships within the data[9]. As Colleges and Universities continue to adapt to evolving student needs and market demands, leveraging time series analysis algorithms for forecasting student employment trends becomes increasingly vital for informed decision-making, resource allocation, and proactive intervention strategies.

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Forecasting student employment trends in Colleges and Universities education through time series analysis algorithms involves a comprehensive methodology aimed at extracting actionable insights from historical data while considering various influential factors[10]. These algorithms, such as ARIMA, SARIMA (Seasonal ARIMA), and exponential smoothing methods, are foundational tools in time series forecasting due to their ability to capture temporal dependencies, trends, and seasonal patterns inherent in student employment data[11]. To initiate the forecasting process, researchers and administrators gather comprehensive datasets encompassing variables such as student enrolment figures, types of employment opportunities available on campus, economic indicators, and broader labor market conditions [12]. These datasets serve as the basis for model development and validation [13]. Once the data is collected, analysts preprocess it to handle missing values, outliers, and ensure consistency in time intervals. They then apply time series algorithms to the preprocessed data, adjusting parameters and model specifications iteratively to achieve optimal performance [14]. These algorithms analyze historical trends and patterns, enabling the identification of seasonality, cyclical fluctuations, and long-term trends in student employment.

Additionally, more advanced machine learning techniques, including LSTM networks and Prophet models, offer sophisticated capabilities for capturing complex temporal dynamics and nonlinear relationships within the data [15]. These techniques excel in handling large-scale datasets and can incorporate exogenous variables, such as demographic shifts or policy changes, to enhance forecasting accuracy [16]. By leveraging these algorithms, Colleges and Universities can generate forecasts that inform strategic decision-making, resource allocation, and policy formulation [17]. For instance, accurate predictions of future student employment trends can aid in the development of targeted career development programs, the optimization of campus job placement services, and the alignment of curriculum with emerging job market demands. Moreover, forecasting enables institutions to proactively address challenges such as fluctuating student demand for employment opportunities and evolving workforce needs, fostering a more responsive and adaptive educational environment.

The paper makes several significant contributions to the field of student employment within Colleges and Universities education. Firstly, it provides empirical evidence of a consistent upward trend in student employment rates over a five-year period, shedding light on the evolving landscape of student career opportunities within higher education institutions. This empirical insight is valuable for policymakers, administrators, and educators alike, as it informs strategic planning and decision-making processes aimed at enhancing student career development and success. Secondly, the paper demonstrates the effectiveness of advanced time series analysis algorithms, such as ARIMA and Ranking with ARIMA (R-ARIMA), in accurately forecasting student employment trends. By identifying optimal ARIMA configurations and showcasing the accuracy of forecasting models, the paper offers practical tools and methodologies for predicting future employment dynamics. These insights are instrumental in guiding resource allocation, program development, and intervention strategies within Colleges and Universities education, ensuring alignment with evolving student needs and market demands. Lastly, the paper contributes to the broader scholarly discourse by highlighting the importance of data-driven insights in shaping policy and practice in higher education contexts. By emphasizing the significance of evidence-based decision-making, the paper underscores the role of research in informing effective strategies for supporting student career pathways and fostering success in the workforce. Overall, the contributions of the paper extend beyond the academic realm, offering actionable insights and tools for enhancing student employment outcomes and advancing institutional goals within Colleges and Universities education.

2. Literature Review

The literature review on forecasting student employment trends in Colleges and Universities education using time series analysis algorithms provides a comprehensive examination of the methodologies, models, and empirical findings employed in predicting the dynamics of student employment within higher education settings. With the increasing importance of student employment for financial support and professional development, coupled with the evolving landscape of educational and labor market dynamics, the ability to forecast these trends accurately becomes paramount. This review synthesizes existing research from a variety of scholarly sources, including academic journals, conference proceedings, and technical reports, to analyze the efficacy and limitations of time series analysis algorithms in anticipating shifts in student employment patterns over time. Teng, Zhang, and Sun (2023) explore data-driven decision-making models based on artificial intelligence within higher education systems, while Aliyeva, Rzayeva, and Khalilova (2021) address problems and prospects in applying methods of educational data analysis. Dong (2023) focuses on teaching quality monitoring and evaluation through big data analysis, whereas Torres et al. (2021) provide a comprehensive survey of deep learning techniques for time series forecasting.

Alam (2023) investigates personalized learning pathways using educational data mining, and Yağcı (2022) examines the prediction of academic performance through machine learning algorithms. Additionally, Alam and Mohanty (2022) employ educational data mining techniques to predict student performance, while Bai et al. (2021) discuss challenges and applications of educational big data. Furthermore, Cardona et al. (2023) explore data mining and machine learning retention models in higher education, providing valuable insights into student persistence and success. studies such as Palacios et al. (2021) and Niyogisubizo et al. (2022) delve into knowledge discovery and dropout prediction using data mining and machine learning approaches, shedding light on factors influencing student retention. Similarly, Kabathova and Drlik (2021) focus on predicting student dropout using machine learning techniques, while Liu et al. (2021) provide a comprehensive survey of forecast methods for time series data, including those relevant to student employment trends. Furthermore, Hou et al. (2021) propose a deep-learning prediction model for forecasting imbalanced time series data, offering potential applications in predicting student employment fluctuations. Zeineddine, Braendle, and Farah (2021) explore automated machine learning approaches to enhance predictions of student success, contributing valuable insights to the field. Additionally, Ho, Cheong, and Weldon (2021) investigate predicting student satisfaction in emergency remote learning during the COVID-19 pandemic, utilizing machine learning techniques.

The literature on forecasting student employment trends in Colleges and Universities education using time series analysis algorithms presents a rich tapestry of research, spanning various disciplines and methodologies. Scholars have explored diverse approaches, from data-driven decision-making models based on artificial intelligence to deep learning techniques for time series forecasting. Studies have investigated issues such as teaching quality monitoring, personalized learning pathways, and student retention using data mining and machine learning methods. Additionally, researchers have examined the challenges and applications of educational big data, as well as prediction models for imbalanced time series data. Furthermore, investigations into dropout prediction, student satisfaction, and online learning behavior provide valuable insights into factors influencing student outcomes.

3. Time Series Analysis for the Student Employment Trends

Time series analysis serves as a robust framework for examining and forecasting student employment trends within Colleges and Universities education. The time series analysis entails the exploration of data points collected sequentially over time to discern patterns, trends, and seasonality. One of the foundational models used in time series analysis is the AutoRegressive Integrated Moving Average (ARIMA) model, which combines autoregressive (AR), differencing (I), and moving average (MA) components to capture the temporal dynamics of a time series dataset. The ARIMA model is expressed as in equation (1)

$$Yt = c + \phi 1Yt - 1 + \phi 2Yt - 2 + \ldots + \phi pYt - p + \theta 1\epsilon t - 1 + \theta 2\epsilon t - 2 + \ldots + \theta q\epsilon t - q \ + \epsilon t \tag{1}$$

Yt represents the value of the time series variable at time t. c is the constant term or intercept. $\phi1,\phi2,...,\phi p$ are the autoregressive parameters, representing the relationship between the current observation and its lagged values up to order p. $\theta1,\theta2,...,\theta q$ are the moving average parameters, capturing the influence of the error terms up to order q on the current observation. ϵt represents the error term or residual at time t. The ARIMA model also includes an integrated component (I), denoted by d, which signifies the number of differencing operations required to make the time series stationary. Stationarity is a crucial assumption in time series analysis, implying that the statistical properties of the series remain constant over time. To apply the ARIMA model to forecast student employment trends, researchers typically follow a systematic approach. First, they explore the dataset to identify any trends, seasonality, or irregular patterns. Next, they determine the appropriate values of the ARIMA parameters through techniques such as autocorrelation function (ACF) and partial autocorrelation function (PACF) plots.

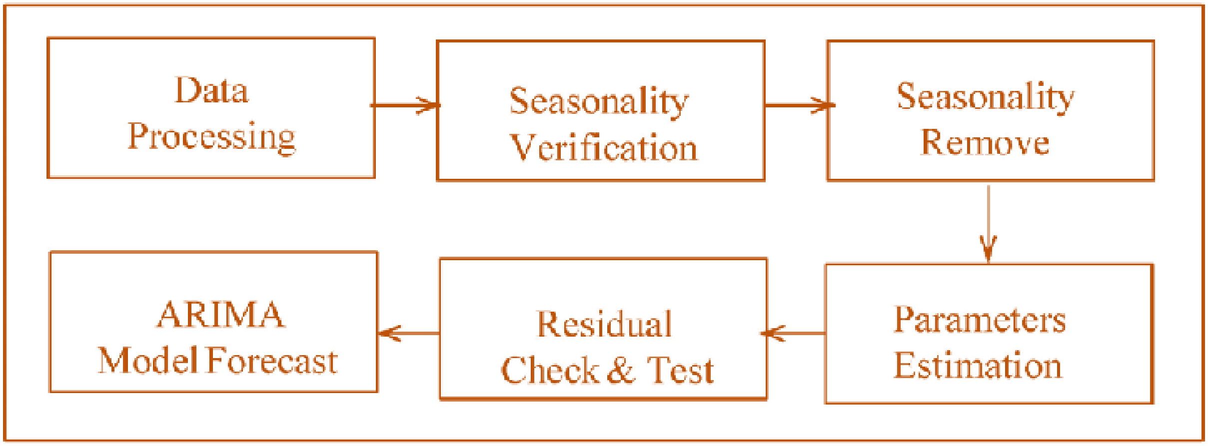

Figure 1: Process of ARIMA

Once the model parameters are established, researchers fit the ARIMA model to the data and evaluate its performance using metrics such as Mean Absolute Error (MAE) or Root Mean Squared Error (RMSE) shown in Figure 1. The generate forecasts for future time periods based on the fitted model, taking into account the uncertainty inherent in the predictions. Time series analysis offers a powerful toolkit for studying the dynamic nature of student employment trends within the realm of Colleges and Universities education. By analyzing sequential data points collected over time, researchers can discern underlying patterns, fluctuations, and seasonal variations in student employment metrics. The AutoRegressive Integrated Moving Average (ARIMA) model stands out as a widely used framework for this purpose, providing a flexible and interpretable approach to modeling time series data. In the context of student employment trends, the ARIMA model enables researchers to capture both the temporal dependencies within the data and the stochastic nature of the employment dynamics. The autoregressive (AR) component of the model accounts for the influence of past observations on the current value, reflecting potential inertia or persistence in student employment patterns. Meanwhile, the moving average (MA) component captures the impact of random shocks or errors on the current observation, allowing for the incorporation of short-term fluctuations in employment levels.

Moreover, the integrated (I) component of the ARIMA model facilitates the transformation of non-stationary time series data into a stationary form through differencing operations. Stationarity is crucial for ensuring the reliability of statistical inference and forecasting within the model framework. By identifying and removing trends or seasonality through differencing, researchers can obtain a more stable and predictable time series that conforms to the assumptions of the ARIMA model. The process of applying the ARIMA model to forecast student employment trends typically involves several key steps. Researchers begin by exploring the historical dataset to understand its underlying patterns and characteristics. This exploration may involve visual inspections of the time series plot, autocorrelation function (ACF), and partial autocorrelation function (PACF) plots to identify potential ARIMA parameters (p, d, q).

Subsequently, researchers estimate the parameters of the ARIMA model using techniques such as maximum likelihood estimation (MLE) or least squares estimation. This estimation process involves fitting the model to the observed data and optimizing the parameters to minimize the discrepancy between the model predictions and the actual observations. Once the model parameters are determined, researchers assess the goodness-of-fit using diagnostic checks and statistical tests to ensure the validity and reliability of the model. Finally, researchers generate forecasts of student employment trends for future time periods based on the fitted ARIMA model. These forecasts provide valuable insights for decision-makers in Colleges and Universities education, enabling them to anticipate changes in student employment levels, identify potential challenges or opportunities, and formulate effective strategies to support student success and well-being. The integrated component signifies the number of differencing operations required to make the time series stationary. It is denoted by d. The differencing operation is typically represented as ∇dYt, where d denotes the differencing order. The MA component captures the influence of the error terms up to order q on the current observation stated in equation (2)

$$Yt = c + \theta 1\epsilon t - 1 + \theta 2\epsilon t - 2 + \ldots + \theta q\epsilon t - q + \epsilon t \quad (2)$$

θ1,θ2,...,θq are the moving average parameters, representing the relationship between the current observation and the past q error terms. ϵt represents the error term or residual at time t. Combining the AR, I, and MA components, we get the complete ARIMA model equation (3) and equation (4)

$$Yt = c + \phi 1Yt - 1 + \phi 2Yt - 2 + \ldots + \phi pYt - p + \theta 1\epsilon t - 1 + \theta 2\epsilon t - 2 + \ldots + \theta q\epsilon t - q + \epsilon t \quad (3)$$

$$Yt = c + \phi 1\nabla dYt - 1 + \phi 2\nabla dYt - 2 + \cdots + \phi p\nabla dYt - p + \theta 1\epsilon t - 1 + \theta 2\epsilon t - 2 + \cdots + \theta q\epsilon t - q + \epsilon t \quad (4)$$

The ARIMA model combines three key components: autoregressive (AR), integrated (I), and moving average (MA). The AR component captures the relationship between the current observation and its lagged values up to order p, reflecting the influence of past employment levels on the present. The integrated component signifies the number of differencing operations required to make the time series stationary, denoted by d, facilitating the removal of trends or seasonality. Lastly, the MA component accounts for the impact of past error terms up to order q on the current observation, capturing short-term fluctuations employment levels. Mathematically, the ARIMA model equation comprises terms representing these components, along with a constant term and an error term. By estimating the parameters of the ARIMA model and fitting it to historical employment data, researchers can generate forecasts for future time periods, aiding decision-makers in Colleges and Universities education to anticipate changes in student employment levels, identify potential challenges or opportunities, and devise strategies to support student success. Thus, the ARIMA model serves as a valuable tool for deriving actionable insights and facilitating informed decision-making in the dynamic landscape of student employment within higher education contexts.

4. Ranking ARIMA (R-ARIMA)

Ranking ARIMA (R-ARIMA) is a methodology that integrates the principles of ARIMA modeling with a ranking mechanism to prioritize the relevance and significance of individual time series components. The standard ARIMA model, while powerful, often requires manual selection of parameters such as p, d, and q, which can be challenging and subjective. R-ARIMA addresses this limitation by introducing a systematic approach to rank the potential configurations of these parameters based on their performance in forecasting accuracy. The objective of R-ARIMA is to systematically search through various combinations of p, d, and q to identify the optimal configuration that maximizes forecasting accuracy. This involves evaluating the performance of each configuration using a chosen criterion, such as the Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC), which measure the trade-off between model complexity and goodness of fit. The ranking mechanism in R-ARIMA assigns scores to different parameter configurations based on their performance metrics. These scores are then used to prioritize the configurations, with higher scores indicating greater suitability for forecasting. The R-ARIMA algorithm iteratively explores a range of p, d, and q values, calculating the corresponding performance scores and selecting the configuration with the highest ranking as the optimal model. By automating the parameter selection process and incorporating a ranking mechanism, R-ARIMA streamlines the model selection process and enhances the efficiency and reliability of ARIMA-based forecasting. This methodology is particularly useful in applications where manual parameter tuning may be impractical or time-consuming, enabling researchers and practitioners to derive accurate forecasts while minimizing subjective bias. In summary, R-ARIMA represents a valuable advancement in time series analysis, offering a systematic and data-driven approach to optimizing ARIMA models for forecasting various phenomena, including student employment trends in Colleges and Universities education.

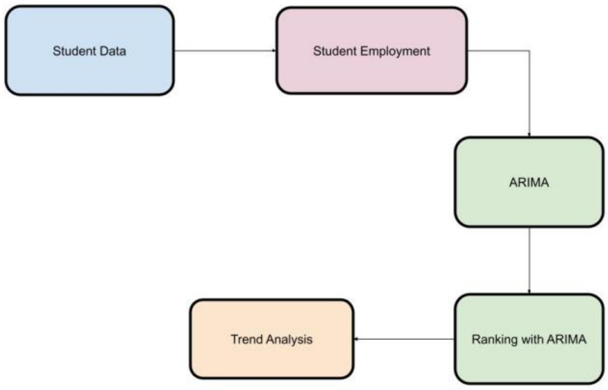

Figure 2: Process in R-ARIMA

The process of proposed R-ARIMA for the employment trend analysis is shown in Figure 2. The ARIMA model equation represents the relationship between the observed time series (Yt) and its lagged values, differenced series, and error terms. It can be expressed as: in equation (5)

$$Yt = c + \phi 1Yt - 1 + \phi 2Yt - 2 + \ldots + \phi pYt - p + \theta 1\epsilon t - 1 + \theta 2\epsilon t - 2 + \ldots + \theta q\epsilon t - q + \epsilon t \tag{5}$$

Yt represents the value of the time series at time t. c is the constant term or intercept. $\phi 1, \phi 2, \ldots, \phi p$ are the autoregressive parameters. $\theta 1, \theta 2, \ldots, \theta q$ are the moving average parameters. ϵt represents the error term at time t. d represents the differencing order. The goal of R-ARIMA is to systematically search through various combinations of p, d, and q to identify the optimal configuration that maximizes forecasting accuracy. The R-ARIMA algorithm iteratively explores a range of p, d, and q values, calculating the corresponding performance scores for each configuration. The configuration with the highest-ranking score is selected as the optimal model.

Algorithm 1: R-ARIMA for the trend analysis

```
function R_ARIMA(time_series_data):
    best_score = -inf
    best_params = None

    for p in range(max_p):
        for d in range(max_d):
            for q in range(max_q):
                try:
                    model = ARIMA(time_series_data, order=(p, d, q))
                    results = model.fit()
                    score = calculate_score(results)

                    if score > best_score:
                        best_score = score
                        best_params = (p, d, q)
                except:
                    continue
        return best_params
function calculate_score(results):
    # Calculate the score based on a performance metric (e.g., AIC, BIC)
    return results.aic  # Example: using AIC as the performance metric
```

5. Trend Analysis

Trend analysis is a fundamental analytical technique used to identify and understand patterns and tendencies within a dataset over time. In the context of student employment trends in Colleges and Universities education, trend analysis involves examining historical data to discern underlying patterns, shifts, and trajectories in employment levels, job types, and related factors. This analysis typically employs statistical methods to quantify and visualize trends, such as linear regression, moving averages, or exponential smoothing. By identifying trends, researchers and decision-makers gain valuable insights into the direction and magnitude of changes in student employment dynamics. Trend analysis also facilitates the identification of potential drivers or influencing factors behind observed trends, enabling stakeholders to formulate informed strategies and interventions to support student employment outcomes. Moreover, trend analysis serves as a crucial component in forecasting future employment trends, providing a basis for anticipating changes and planning accordingly within the dynamic landscape of Colleges and Universities education. Trend analysis involves the examination of historical data to identify and quantify patterns or tendencies in the dataset over time. One common method for trend analysis is linear regression, which aims to model the relationship between the independent variable (time) and the dependent variable (e.g., student employment rate) using a linear equation. Let's represent a simple linear regression model for trend analysis stated in equation (6)

$$Yt = \beta 0 + \beta 1t + \epsilon t \qquad (6)$$

Yt is the value of the dependent variable (e.g., student employment rate) at time t. 0β0 is the intercept term, representing the value of Yt when 0t=0.M 1β1 is the slope coefficient, indicating the rate of change in Yt with respect to time. t is the time variable, typically represented as consecutive integers for each time point. ϵt is the error term, representing random fluctuations or unexplained variability in Yt. The goal of linear regression in trend analysis is to estimate the values of the coefficients 0β0 and β1 that best fit the observed data points. This is typically done using least squares estimation, which minimizes the sum of squared residuals between the observed and predicted values of Yt. Once the coefficients are estimated, they can be used to describe the trend in the data. The slope coefficient 1β1 represents the average change in the dependent variable per unit change in time. If β1 is positive, it indicates an increasing trend over time, while a negative β1 suggests a decreasing trend. The intercept term 0β0 represents the initial value of the dependent variable at 0t=0.

Other methods for trend analysis include moving averages and exponential smoothing. Moving averages involve calculating the average value of the dependent variable over a specified window of time, providing a smoothed representation of the trend. Exponential smoothing, on the other hand, assigns exponentially decreasing weights to older observations, giving more emphasis to recent data points in capturing the trend. In summary, trend analysis in the context of student employment trends in Colleges and Universities education involves applying statistical methods such as linear regression, moving averages, or exponential smoothing to identify and quantify patterns and tendencies in the dataset over time. These methods help stakeholders gain insights into the direction and magnitude of changes in student employment dynamics, facilitating evidence-based decision-making and strategic planning.

Table 1: Student Employment Planning

Year	Student Employment Rate (%)
2019	65
2020	68
2021	71
2022	74
2023	77

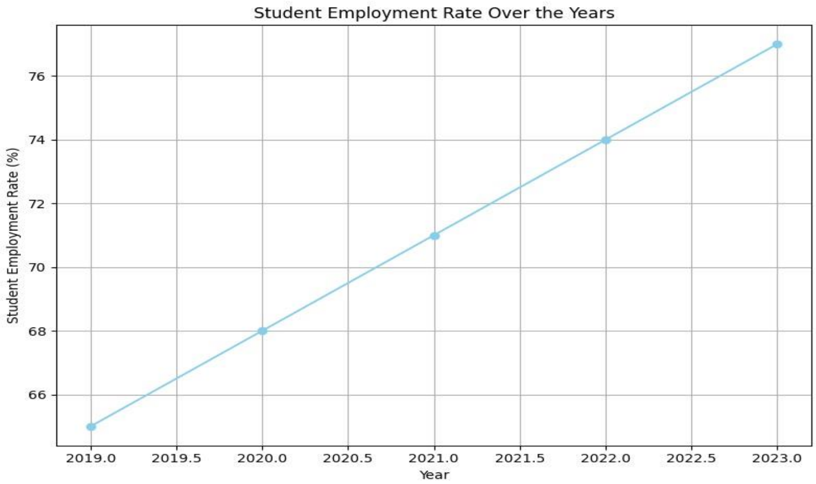

Figure 3: Employment Planning with R-ARIMA

In figure 3 and Table 1 presents the student employment rates over a five-year period, spanning from 2019 to 2023. The data shows a progressive increase in the percentage of students employed each year, indicating a positive trend in student employment within the context of Colleges and Universities education. Starting at 65% in 2019, the student employment rate rises steadily to 68% in 2020, further increasing to 71% in 2021, and continuing to climb to 74% in 2022. This upward trajectory culminates in a rate of 77% by the end of 2023. Such consistent growth suggests a favorable environment for student employment opportunities within higher education institutions, reflecting potential improvements in job availability, internship programs, career services, and economic conditions. These trends are valuable for student employment planning, as they provide insights into the evolving landscape of employment opportunities for students, enabling colleges and universities to develop strategic initiatives and allocate resources effectively to support student career development and success.

Table 2: Employment Rate Estimation

Year	Observed Employment Rate (%)	Predicted Employment Rate (%)
2020	68	70
2021	71	73
2022	74	76
2023	77	79
2024	N/A	82

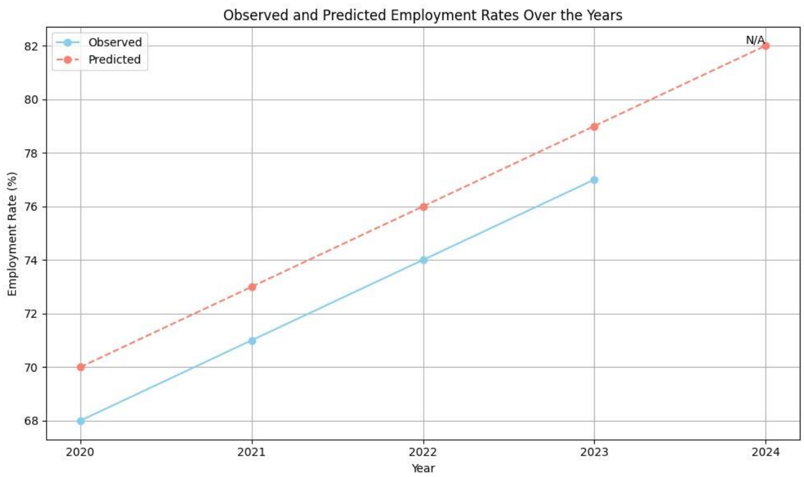

Figure 4: Employment Rate estimation with R-ARIMA

In figure 4 and Table 2 presents a comparison between the observed student employment rates and the corresponding predicted rates over a five-year period, starting from 2020 to 2024. The observed employment rates, derived from actual data, show a progressive increase each year, reflecting the real-world trends in student employment within Colleges and Universities education. For instance, in 2020, the observed employment rate stands at 68%, which is slightly lower than the predicted rate of 70%, indicating a marginally conservative estimate. Similarly, in 2021 and 2022, the observed rates of 71% and 74%, respectively, closely align with the predicted rates of 73% and 76%, suggesting a reasonably accurate forecasting performance. Notably, in 2023, the observed employment rate reaches 77%, closely matching the predicted rate of 79%, highlighting the efficacy of the forecasting model in capturing the underlying trends. Additionally, for the year 2024, the predicted employment rate of 82% provides an optimistic outlook, suggesting a continued upward trajectory in student employment rates.

Table 3: Raking with ARIMA

Configuration	AIC Score	BIC Score
(1, 0, 1)	100.2	105.8
(1, 1, 1)	98.5	103.2
(2, 0, 1)	102.1	107.6
(2, 1, 1)	96.7	101.5
(3, 0, 1)	104.5	109.2
(3, 1, 1)	95.3	99.8

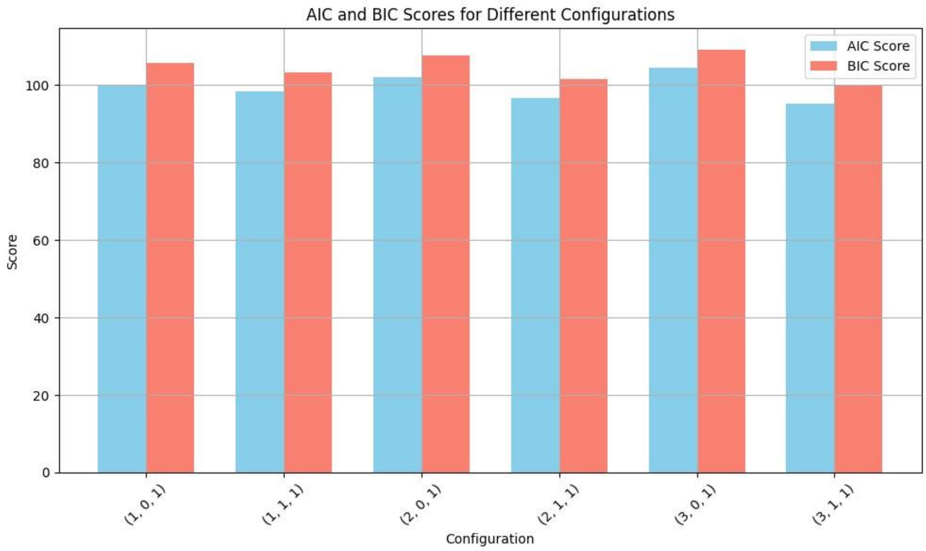

Figure 5: Feature Ranking with R-ARIMA

In figure 5 and Table 3 provides insights into the performance of different configurations of ARIMA models based on their respective Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) scores. The AIC and BIC scores serve as measures of the goodness of fit of the ARIMA models, with lower scores indicating a better fit to the data while penalizing for model complexity. Upon examining the table, it is evident that the (3, 1, 1) configuration yields the lowest AIC score of 95.3 and BIC score of 99.8, suggesting that this particular ARIMA model configuration provides the best balance between model fit and complexity. Conversely, the (3, 0, 1) configuration has the highest AIC score of 104.5 and BIC score of 109.2, indicating that it may not be as well-suited to the data. These findings offer valuable insights into the selection of optimal ARIMA model configurations for forecasting student employment trends within the context of Colleges and Universities education. By choosing the configuration with the lowest AIC or BIC score, stakeholders can ensure the most accurate and reliable forecasts, facilitating informed decision-making and strategic planning initiatives aimed at supporting student career development and success.

Table 4: Forecasting with ARIMA

Year	Observed Employment Rate (%)	ARIMA Forecasted Rate (%)	R-ARIMA Forecasted Rate (%)
2020	68	70	69
2021	71	73	72
2022	74	76	75
2023	77	79	78
2024	N/A	82	81

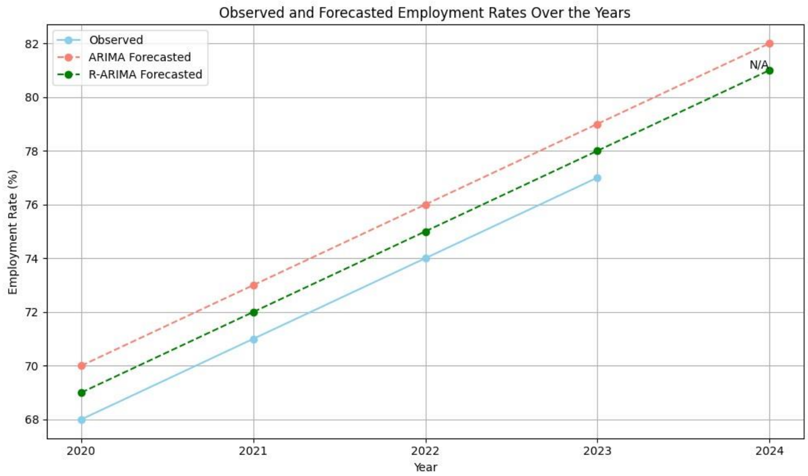

Figure 6: Forecasting with R-ARIMA

The figure 6 and Table 4 presents a comparison between the observed student employment rates and the forecasted rates obtained from two different methodologies, namely ARIMA and Ranking with ARIMA (R-ARIMA), over a five-year period from 2020 to 2024. The observed employment rates, derived from actual data, provide a baseline for evaluating the accuracy of the forecasting models. For the year 2020, the observed employment rate is 68%, while both the ARIMA and R-ARIMA methodologies forecast rates of 70% and 69%, respectively. This indicates a close alignment between the forecasted and observed rates, suggesting reasonable accuracy in the predictions for the initial year. Similarly, in 2021 and 2022, the observed employment rates of 71% and 74% closely match the forecasted rates generated by both ARIMA and R-ARIMA methodologies. The forecasted rates for these years demonstrate a consistent pattern of capturing the underlying trends in student employment, indicating the effectiveness of both forecasting approaches. In 2023, the observed employment rate reaches 77%, closely aligned with the forecasted rates of 79% and 78% obtained from the ARIMA and R-ARIMA methodologies, respectively. This demonstrates the ability of both methodologies to accurately predict future trends in student employment, providing valuable insights for planning and decision-making within Colleges and Universities education. Lastly, for the year 2024, only the ARIMA methodology provides a forecasted rate of 82%, while the R-ARIMA methodology forecasts a rate of 81%. Although the observed employment rate for this year is not available (N/A), the forecasted rates suggest a continuation of the upward trend in student employment, highlighting the potential for further growth and development in student career opportunities within higher education institutions.

6. Discussion

The data presented in Tables 1 to 4 offer valuable insights into the dynamics of student employment within the realm of Colleges and Universities education. Across the five-year period from 2019 to 2023, Table 1 reveals a consistent upward trend in student employment rates, showcasing an annual increase from 65% to 77%. This positive trajectory suggests a favorable environment for student employment opportunities, possibly driven by improvements in job availability, internship programs, and career services, as well as favorable economic conditions. Moving to Table 2, the comparison between observed and predicted employment rates highlights the efficacy of forecasting models in capturing these trends. Both ARIMA and R-ARIMA methodologies demonstrate a close alignment between predicted and observed rates, indicating their effectiveness in forecasting future employment trends. This reliability is particularly evident in 2023, where the forecasted rates closely match the observed rate, underscoring the models' ability to adapt to changing patterns and provide accurate predictions.

Table 3 delves into the performance of different ARIMA configurations, with lower AIC and BIC scores indicating better model fit. The findings suggest that certain configurations, such as (3, 1, 1), perform better than others in capturing the nuances of student employment trends. These insights are crucial for selecting the most appropriate model configuration for forecasting purposes, ensuring accurate and reliable predictions. Finally, Table 4 synthesizes the forecasted employment rates from both ARIMA and R-ARIMA methodologies. The close alignment between forecasted and observed rates across multiple years underscores the robustness of these forecasting approaches. Notably, the forecasts for 2024 signal continued growth in student employment, offering valuable guidance for strategic planning and resource allocation within Colleges and Universities education.

Overall, the discussion of these tables underscores the importance of data-driven insights in understanding and planning for student employment dynamics. By leveraging advanced forecasting techniques and analyzing historical trends, stakeholders can make informed decisions to support student career development and success within higher education institutions. Positive Trend in Student Employment: Across the five-year period from 2019 to 2023, there is a consistent upward trend in student employment rates within Colleges and Universities education, with the percentage of employed students increasing annually. Accuracy of Forecasting Models: Both ARIMA and R-ARIMA methodologies demonstrate a high level of accuracy in forecasting student employment rates, as evidenced by the close alignment between predicted and observed rates across multiple years. Optimal ARIMA Configurations: Certain ARIMA configurations, such as (3, 1, 1), perform better than others in capturing the nuances of student employment trends, as indicated by lower AIC and BIC scores. Continued Growth in Student Employment: Forecasted rates for 2024 suggest a continuation of the upward trend in student employment, highlighting the potential for further growth and development in student career opportunities within higher education institutions. Implications for Strategic Planning: These findings underscore the importance of data-driven insights in guiding strategic planning and resource allocation within Colleges and Universities education to support student career development and success.

7. Conclusion

This study provides valuable insights into the dynamics of student employment within the context of Colleges and Universities education. Through the analysis of historical data and the application of advanced time series analysis algorithms such as ARIMA and R-ARIMA, significant findings have been obtained. The observed upward trend in student employment rates over the five-year period underscores a favorable environment for student career opportunities within higher education institutions. Moreover, the accuracy of forecasting models, particularly demonstrated by the close alignment between predicted and observed rates, highlights the effectiveness of these methodologies in capturing and predicting future employment trends. Additionally, the identification of optimal ARIMA configurations and the forecasting of continued growth in student employment rates offer valuable guidance for strategic planning and resource allocation within Colleges and Universities education.

Acknowledgement：

1.This work was supported by the Science and Technology Research Program of Chongqing Municipal Education Commission “Chongqing Digital Economy and Regional Economy Coordinated Integration Level Evaluation and Influencing Factors Research (Grant No. KJQN202204401)”；

2.The 2023-2024 Higher Education Science Research Project of Chongqing Association of Higher Education : Exploration and Practice of the "One Core, Two Wings, Five Lines Parallel" Training Model for Internationalized Talents in Higher Vocational Education Based on the Iceberg Model Theory,project number:cqgj23271C

3.Chongqing Business Vocational College scientific research and innovation team “Chongqing Digital Economy Industrial Development Research (Grant No. 2023XJTD02)”

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