

## COMPARISON OF THE APPLICATION OF LINEAR REGRESSION WITH SLIDING WINDOW VALIDATION AND K-FOLD CROSS-VALIDATION FOR FORECASTING COVID-19 RECOVERED CASES

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### Abstract

The increase in confirmed cases and deaths due to Covid-10 continues to spread and increase day by day throughout the world. This has resulted in a world health crisis that impacts all sectors of life. The government declared a movement to suppress the spread of Covid-19, so it is necessary to understand the pattern of Covid-19 problems. Researchers contribute scientifically to finding patterns of death or recovery due to COVID-19 by applying Machine Learning methods. The Linear Regression and Sliding Window preprocessing methods are appropriate for forecasting time series data. This research obtained RMSE results at 0.320 with linear regression with sliding window validation and RMSE at 0.320 with linear regression with K-Fold cross-validation. This proves that Linear Regression with Sliding Window Validation can improve performance much better than k-fold cross-validation in forecasting COVID-19 recovery cases in China. The sliding window validation method has been proven to increase accuracy for forecasting with time series data compared to other standard preprocessing methods, namely K-Fold cross-validation. In the future, further research is needed to test different types of time series data by comparing the application of sliding window validation and K-Fold cross-validation or developing other validation models.

Keywords: Covid-19, Forecasting, Linear Regression; Sliding Window Validation

### Abstrak

Peningkatan kasus terkonfirmasi dan kasus kematian akibat Covid-10 terus menyebar dan meningkat dari hari ke hari di seluruh dunia. Hal tersebut mengakibatkan krisis kesehatan dunia yang berdampak pada semua sektor kehidupan. Pemerintah mendeklarasikan gerakan untuk menekan penyebaran Covid-19, sehingga perlunya memahami pola permasalahan Covid-19. Para peneliti berkontribusi secara ilmiah untuk menemukan pola kematian atau kesembuhan akibat Covid-19 dengan penerapan metode Machine Learning. Metode Linear Regression dan metode preprocessing Sliding Window merupakan metode yang tepat untuk peramalan data time series. Pada penelitian ini diperoleh hasil RMSE sebesar 0,320 pada penerapan Linear Regression dengan Sliding Window Validation, dan RMSE sebesar 0,320 pada penerapan Linear Regression dengan K-Fold Cross Validation. Hal tersebut membuktikan bahwa penerapan Linear Regression dengan Sliding Window Validation mampu meningkatkan kinerja yang jauh lebih baik dibanding dengan K-Fold Cross Validation pada peramalan kasus sembuh Covid-19 di China. Metode Sliding Window Validation terbukti meningkatkan akurasi untuk peramalan dengan data time series dibanding dengan metode preprocessing umum lainnya yaitu K-Fold Cross Validation. Di masa depan, diperlukan penelitian selanjutnya untuk menguji pada jenis data time series yang berbeda dengan membandingkan penerapan Sliding Window Validation, K-Fold Cross Validation, atau mengembangkan model Validasi lainnya.

Kata kunci: Covid-19, Forecasting, Linear Regression, Sliding Window Validation

### INTRODUCTION

The COVID-19 virus pandemic that began in December 2019 in China continues to spread daily. The rate of confirmed cases and deaths due to

Covid-19 continues to increase. In a short time, the Covid-19 virus has spread and claimed millions of lives around the world. In Indonesia on March 10, 2021, 1,398,578 (5633 new) confirmed cases of COVID-19 were reported, 37,932 deaths (175 new)



and 1,216,433 recovered cases from 510 districts in 34 provinces (WHO, 2021). In Malaysia, as of April 30, 2020, 69.49% have been cured, and a 1.7% death rate from 6,002 Covid-19 cases (Norwawi, 2021). On July 7, 2020, the World Health Organization (WHO) reported that COVID-19 had infected more than 11 million people worldwide and killed more than 500 thousand of them (Yalçinkaya et al., 2021).

The spread and increase in cases of the COVID-19 virus is causing a massive health crisis worldwide and impacting all areas of life. Governments worldwide announced Movement Control Orders (MCOs) to suppress the chain of spread of COVID-19 (Norwawi, 2021). There is a need to understand the spread pattern of COVID-19 to predict the number of COVID-19 cases (Fanelli & Piazza, 2020) and take precautions as quickly as possible (Rath et al., 2020). It is essential to model mortality rates in the fight against COVID-19, so scientific contributions are needed to apply research methodologies in the fight against COVID-19 (Yalçinkaya et al., 2021). Therefore, researchers have forecasted the COVID-19 problem by using machine learning methods. Machine learning (ML) methods help predict COVID-19 features to prevent and manage disease outbreaks (Kavadi et al., 2020). Metode peramalan yang telah diterapkan oleh para peneliti seperti dengan metode Neural Network (Saba & Elsheikh, 2020) (Chimmula & Zhang, 2020) (Baalamurugan & Phutela, 2024) dan metode Linear Regression (Rath et al., 2020) (Yalçinkaya et al., 2021) (Sanghatawatana et al., 2023).

Developing forecasting models to predict the spread of COVID-19 is a critical issue (Saba & Elsheikh, 2020). Arima is also a standard method used for forecasting (Özen, 2024). However, Priya et al.'s research showed that Linear Regression was better than Arima's (Priya et al., 2024). The lowest regression coefficient results from the linear regression model compared to the neural network, which can help linear regression analyze the value of information flow in the manufacturing chain effectively (Biyeme et al., 2023). Linear regression models are top-rated and widely used in various fields of science (Yalçinkaya et al., 2021). Linear Regression models deliver outstanding accuracy in COVID-19 forecasting (Rath et al., 2020). Forecasting performance with linear regression models provides the highest accuracy and robustness among all tested models (Fang & Lahdelma, 2016). Among other models, Linear Regression is the most promising model because of its accuracy and simple application, especially for time series data. The time interval of the data becomes a relevant factor that determines the

quality of the Linear Regression model (Fumo & Rafe Biswas, 2015).

Time series data is needed for future forecasting, especially the Covid-19 pandemic. Time series data collected from 10 countries of confirmed, recovered, and COVID-19 death cases have been used to build models efficiently and accurately (Castillo & Melin, 2020). A set of data in a certain period that each data point has the same distance as long as it is called time series data (Chimmula & Zhang, 2020). Time series data is used to study trends and predict events. Time series forecasting primarily aims to analyze the past and predict the future with developed models (Norwawi, 2021).

One of the most widely used evaluation models is K-fold cross-validation. However, the cross-validation model is sometimes not valid for forecasting in time series models but is more appropriate for classification and regression cases (Bergmeir et al., 2018). Several studies have shown that Cross Validation fails in long-term contexts, as in the research (Opsomer et al., 2001), which indicates that Cross Validation reduces the bandwidth in the kernel estimator regression framework if there is autocorrelation, the error is high, so the method exceeds the data. The inherent serial correlation and potential non-stationarity of the data means that its application is not easy for time series forecasting (Bergmeir et al., 2018).

It was a Sliding Window into a stable model for long-term forecasting (Davtyan et al., 2020). The Sliding Window method is applied to forecasting time series data (Norwawi, 2021). The sliding window has improved forecasting performance (Papadopoulos et al., 2023). The sliding Window model proposed a model for time series data that avoids learning complex problems of varying time delays (Hao et al., 2020). The Sliding method is appropriate for integrating relevant variables into a time series matrix, providing time characteristics for prediction models and avoiding complicated time delay calculations (Hao et al., 2020). A sliding window is an estimation method that effectively improves accuracy because it can adaptively select the sliding window size to observe and capture the latest trends in the data. Pérez-Solano et al. applied Sliding Window to linear regression to synchronize time in wireless networks (Pérez-Solano & Felici-Castell, 2015). A sliding window is a preprocessing method. Applying the training data approach using the Sliding Window proved to significantly improve the accuracy achieved compared to similar models (Papadopoulos et al., 2023).

The Linear Regression and Sliding Window preprocessing methods are suitable for forecasting

time series data because they are proven to achieve high accuracy. Therefore, this study will apply a combination of the two methods, namely the Linear Regression method with Sliding Window Validation, for forecasting the recovery rate in COVID-19 patients. Then, K-Fold cross-validation will be compared with another standard preprocessing method to prove its accuracy. So which performance will be better between the application of Linear Regression with Sliding Window Validation and Linear Regression with K-Fold Cross Validation?

## MATERIALS AND METHODS

### Data

The dataset is taken from public data on kaggle.com. The dataset is time series data for the number of recovered cases of COVID-19 in China from January 22, 2020, to May 10, 2020. Table 1 shows the attributes in the Time Series Data of COVID-19 Recovered Cases in China consisting of 1 predictor attribute, namely date, and class attribute, namely the number of recoveries per date.

Table 1. Time Series Data for Covid-19 Recovered Cases in China

No	Attribute	Information
1	Date	Date
2	Case Cured	Number of recoveries per date

### Methodology

The method applied in this study is conducting two experiments with the Covid-19 Time Series Dataset in China, as shown in Figure 1. The experiment uses linear regression with sliding window validation and linear regression with K-Fold cross-validation to predict the number of cases cured over time in a certain period. After running the training and testing process with Linear Regression with Sliding Window Validation and Linear Regression with K-fold cross-validation, a Root Mean Square Error (RMSE) will be generated. RMSE is a good evaluation metric when the error distribution follows a normal distribution. This article also discusses RMSE as a more discriminative metric than MAE because it is sensitive to large errors, which is important in various fields, including geosciences (Chai & Draxler, 2014). RMSE provides a clear understanding of model performance by measuring the average deviation from actual values (Botchkarev, 2019). Then, from the RMSE results in the two experiments, comparisons will be made to

determine the most negligible RMSE results. The most minor RMSE result is the best result.

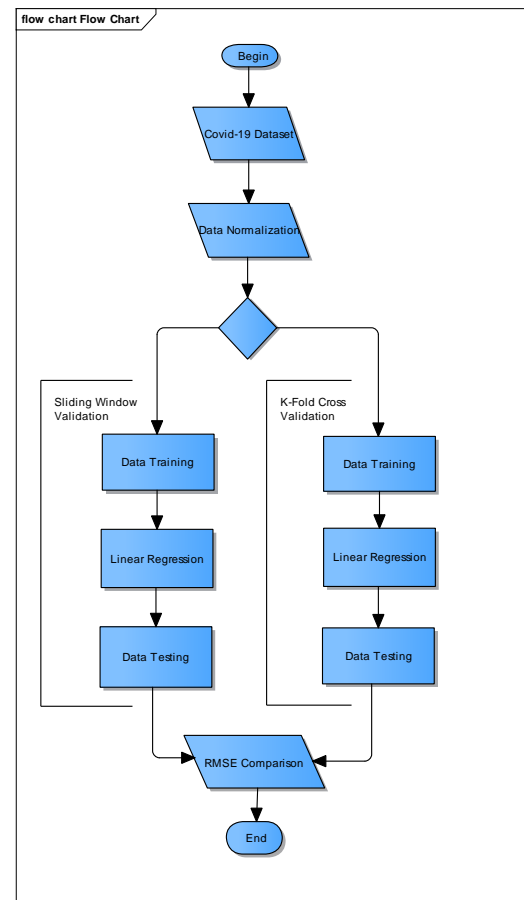


Figure 1. Comparison of Application of Linear Regression with Sliding Window Validation and Linear Regression with K-Fold Cross Validation

The differences in the Sliding Window Validation and K-Fold Cross Validation process are shown in Figure 2 and Figure 3. Figure 2 shows the Sliding Window Validation Process, starting from the 1st data to the 5th, which is used to predict the 6th data. The second segment begins from the 2nd data up to the 6th data used to predict the 7th data. This process continues until all the observation data has been segmented (Z. Chen & Yang, 2004). Sliding Window Validation divides the dataset into two parts, one for initial training and another for testing. The training window shifts across the data, and the model updates iteratively over time (Filho, 2023).

Figure 3 shows how K-Fold Cross Validation works by dividing the dataset into  $k=10$  folds of equal size. The model is trained using the  $k-1$  fold as training data (white color block) and test data (red color block) on the remaining folds. The training and testing process is repeated  $k$  (10) times, with each fold used as test data exactly once

(Wibowo, 2017). In K-fold Cross-Validation, dataset splitting is done by dividing the dataset into folds. At the same time, Sliding Window Validation focuses on splitting data based on time spans for testing and training, respectively (Mustafa Qamar-ud-Din, 2019).

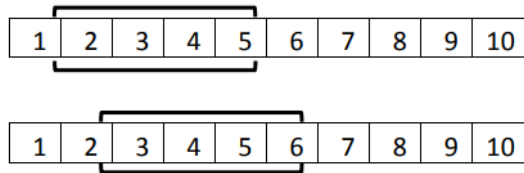


Figure 2. Siding Window Validation Process  
Source: (Wahyuni, 2021)

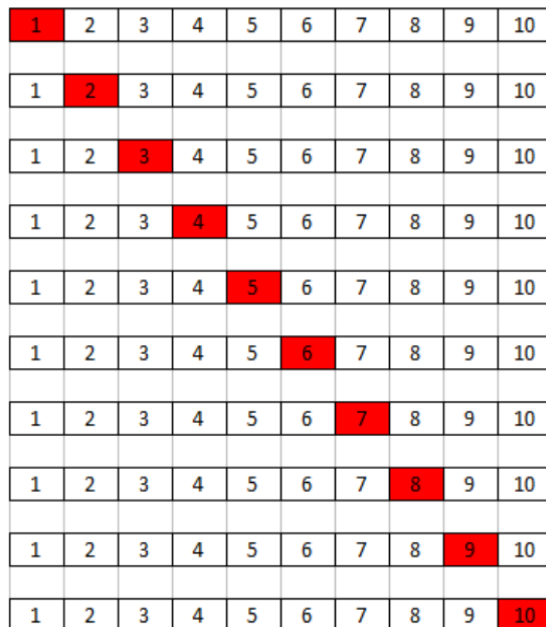


Figure 3. K-Fold Cross Validation Process  
Source: (Wibowo, 2017)

## Linear Regression

Linear regression is used to characterize the impact of selected predictor variables on response variables (Fang & Lahdelma, 2016). Linear regression applied to numerical data modeling (Han et al., 2012). There are two Linear Regressions according to the complexity of the relationships between variables, namely Simple Linear Regression and Multiple Linear Regression. Simple linear regression is the relationship between one response variable and one predictor variable (Fumo & Rafe Biswas, 2015). Multiple Linear Regression is the relationship between one response variable and multiple predictor variables (Shao et al., 2020).

Simple Linear Regression has the following equation:

$$Y = \beta_0 + \beta_1 + \varepsilon \dots\dots\dots(1)$$

Y is the response variable, X is the predictor variable,  $\beta_0$  and  $\beta_1$  are the regression coefficients or regression parameters, and  $\epsilon$  is the error to account for the difference between the predicted data from equation (1) (Fumo & Rafe Biswas 2015).

## Sliding Window

A sliding window is a method performed at the preprocessing stage to restructure data into classification problems according to time series (Norwawi, 2021). How sliding windows work can effectively use new data to update model parameters and reflect recent changes in capacity trends so that forecasted capacity gradually converges with actual capacity (L. Chen et al., 2020). The sliding window slides along the sequence and observes the pattern at random. The selected position is defined as the pattern support. The main problem with the sliding window technique is removing the expiration result from the currently created model (Brockmann et al., 2006). The main reason for choosing the sliding window method is that time series data is a single variable that changes over time. Continuously- these data are bound to each other, meaning that what happens at time  $t$  will be very dependent or influenced by what happened at the previous time, such as  $y(t)=f(y(t-n))$ , where  $n$  is the period we will investigate, as in Figure 2 which is the concept of Sliding Window.

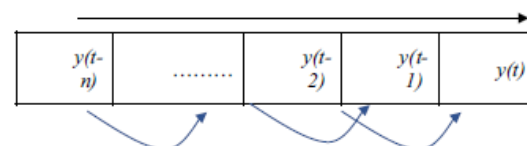


Figure 2. Sliding Window Validation Concept

## RESULTS AND DISCUSSION

Two experiments were conducted. Namely, the application of Linear Regression with Sliding Window Validation and Linear Regression with K-fold cross-validation on the Time Series Dataset of COVID-19 recovered Cases in China. Then, the final result, i.e., the RMSE of the two method mergers, will be compared.

Table 2 shows the RMSE results in applying Linear Regression with Sliding Window Validation of 0.320, while the Linear Regression with K-Fold Cross Validation of 0.975.



Table 2. Comparison of RMSE Results on the Application of Linear Regression with Sliding Window Validation and Linear Regression with K-Fold Cross Validation

No	Method	RMSE
1	Linear Regression dengan Sliding Window Validation	0.320
2	Linear Regression dengan K-Fold Cross Validation	0.975

The comparison results in Table 2 show significant differences in the application of Linear Regression with Sliding Window Validation and Linear Regression with K-fold cross-validation. There is a substantial decrease in RMSE value when using the Sliding Window method compared to K-Fold cross-validation. The purpose of the sliding Window is to reduce approximation errors (e.g., Euclidean or vertical distance between approximations of the actual one with the time series). This error limit is represented by how many parameters are used in a time series (BenYahmed et al., 2015). As Hao et al. said, Sliding Window can solve the complex problem of varying time delays in time series data (Haos et al., 2020). It can improve performance and accuracy (Papadopoulos et al., 2023). This proves that using the sliding Window preprocessing method for forecasting time series data can increase performance much more than other preprocessing methods, such as K-Fold cross-validation. Previous research shows that Sliding Windows can solve complex problems such as varying time delays in time series data and improve performance and accuracy.

## CONCLUSIONS

Experiments have been conducted on applying Linear Regression with Sliding Window Validation and Linear Regression with K-Fold Cross on the Time Series Dataset of COVID-19 recovered Cases in China. RMSE of 0.975 was obtained in Linear Regression with K-Fold cross-validation and RMSE of 0.320 in Linear Regression with Sliding Window Validation. The application of Linear Regression with Sliding Window Validation shows a much smaller RMSE value than Linear Regression with K-Fold Cross Validation. This experiment shows that the Sliding Window preprocessing method can improve performance for forecasting time series data compared to other preprocessing methods, such as K-Fold Cross-Validation. Sliding Window can overcome problems with time series data, namely varying time delays and reducing

errors in the vertical distance between the actual approximation and the time series.

However, this study only used 1 dataset for the experiment, and only two variables were in the time series data. So, results may differ when conducting experiments with different types of time series data or with a more significant number of variables. For this reason, further research is needed to apply sliding window validation and K-Fold cross-validation or develop other validation models for different types of time series data.

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