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Support Vector Regression Analysis for Electricity Load

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ABSTRACT

Need or consumption of electricity in various regions from time to time are always different, so that the supply of electric power and generators are used also differ from one area to another. Predictions from this need for electricity can help electrical energy service providers, so that the demand for electricity and the availability of electricity is balanced. A Support Vector Machine (SVM) technique called Support Vector Regression is applied in regression cases. Overfitting can be addressed using the SVR approach, resulting in strong performance, results with good generalization and accuracy. The Radial Basis Function (RBF) and the Linear Function are the kernel functions employed in this study. The purpose of this research is model prediction and forecasting on time series data. The results obtained in this study are the model formed from the training data has a good performance in forecasting the test data.

Keywords: Support Vector Regression, Radial Basis Function Kernel, Linear Function Kernel, Time Series

1. INTRODUCTION

Electricity is a form of energy that affects life and human life today. Electrical energy is the main energy needed for equipment electricity with the provisions of consumption needs electric power in Watts (W) to drive motors, lights lighting, heating, cooling or for re-activating a mechanical device for producing other forms of energy [1]. The development of science and technology, produce new discoveries that are needed electricity as a source of energy, so it increases too electricity needs in life. Need or consumption of electricity in various regions from time to time are always different, so that the supply of electric power and generators are used also differ from one area to another. The need for electrical energy tends to change every day, so that The State Electricity Company (PT. PLN) as the sole provider of electrical energy must be able to predict the need for electricity load every day. Predictions from this need for electricity can help electrical energy service providers (PT. PLN) so that the demand for electricity and the availability of electricity is balanced. So that doesn't happen a waste of the cost of generating electrical energy due to the power that is sent from it generator is greater than demand, or the outage does not occur due to the electricity demand is greater than expected, which if this happens it will be detrimental to the provider or consumer.

Regression is a data mining approach that forecasts the value of a variable based on the value of another variable, where the predictor variable is an attribute that is known and the response variable is the value that has to be forecasted [2]. Support Vector Regression is one of the techniques used in the supervised learning process for regression (SVR). A Support Vector Machine (SVM) technique called Support Vector Regression is applied in regression cases. The SVR approach has been used in numerous studies to solve forecasting scenarios with good accuracy in comparison to other methods. In order to create strong performance and benefits in optimizing the pattern recognition system with good generalization and accuracy results, SVR is a technique that can overcome overfitting [3]. In time series patterned data, or the collection of observations of ordered data across time, SVR is utilized. An investigation of the pattern of the relationship between the variables to be estimated and the time variable is used to forecast using the time series approach. When predicting a time series of data, it is important to consider the kind or pattern of the data. Time series data patterns often fall into one of four categories: horizontal, trend, seasonal, or cyclical [4].

When used to create SVM, Support Vector Regression (SVR) exhibits consistent performance in the prediction or forecasting of time series data [2]. Support vector regression (SVR) is successfully employed in a variety of study disciplines, including the prediction of stock price movement data, among others. A comparison reveals that SVR outperforms multilayer perceptron (MLP) networks for a short-term prediction in terms of the mean square error [3], Cross validation (CV) is a notion used in the grid search algorithm method, which has SVR's ideal parameters. This approach's accuracy is 92.47% for training data and 83.39% for testing data [4] [5], predictive sales data, among others, Support Vector Regression (SVR) to predict the house prices in King County, USA, produce best accuracy is a coefficient of determination (R-squared) of 0.86 with a radial basis kernel function and a C value of 10 the result [6], High-frequency components perform better at forecasting short-term horizons when empirical mode decomposition (EMD) and support vector regression (SVR) are combined, while low-frequency components perform better at forecasting long-term horizons [7], traffic data prediction, that is [8] [9], [9], the SVR outperformed a moving average strategy and an artificial neural network model [10], A MAPE percentage of 7.95% for the polynomial kernel in the Support Vector Regression Method with two kernels indicates that the method is "Very Good," whereas a MAPE percentage of 13.35% for the RBF kernel indicates that the method is "Good." [11], and many other studies.

Numerous studies have demonstrated that the SVR model performs better in prediction than the artificial neural network (ANN) model [12] [13] One of them uses Support Vector Regression (SVR) analysis to predict PV power plants in various weather scenarios; the model outperforms artificial neural network (ANN) models, persistence models, and other traditional models [14]. The radial basis function (RBF) has been shown to be the best kernel since it exhibits the minimum error value when compared to other kernels, and the reliability of SVR performance is mostly affected by the kernel function employed and the properties of the data utilized in generating the SVR [15] [16] [17] [18]. The Support Vector Regression (SVR) algorithm was applied by comparing the

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kernel radial basis function (RBF) and the polynomial function on predictions and forecasting on stationary time series data, which was based on descriptions of some of the prior research literature that served as the reference in this study.

2. METHOD

The research method is a stage that will produce output or results from research in accordance with the objectives to be achieved. This research has several stages it can be seen in Figure 1.

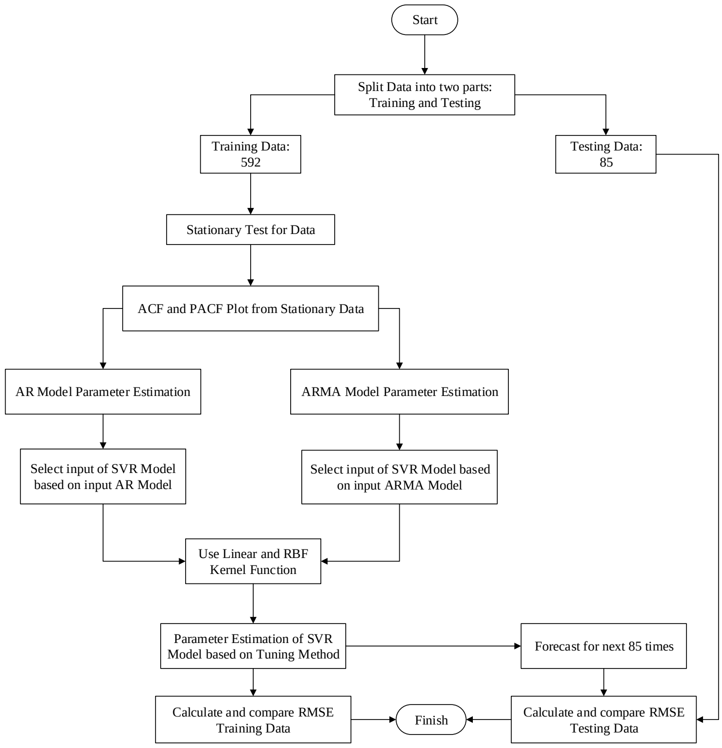

Figure 1 *Flow Chart*

Use input from the ARMA and AR models in this situation for the Support Vector Regression (SVR) analysis's linear and radial basis function (RBF) kernels. This is how the research is explained based on Figure 1:

1. Split data into two parts, namely training and testing;
2. Training consists of 592 data, and 85 data for testing;
3. Stationary test for data;
4. Check ACF and PACF plot from stationary data;
5. AR and ARMA model parameter estimation;
6. Select each input of SVR Model based on input AR model and ARMA model;
7. Use Linear Function Kernel and RBF Kernel;
8. Parameter estimation of SVR Model based on Tuning method; and
9. Forecast for next 85 times.

   Calculate Root Mean Squared Error (RMSE) for training data and testing data.

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2.1. Data

The data used in this example is secondary data, namely a sample of information on the actual daily electrical usage in the Bima region between March 20, 2019, and January 24, 2021, as measured in kilowatts (KW) (PLN). There are 677 observed data (*n*), divided into 592 training data and 85 testing data.

2.2. Support Vector Regression (SVR)

Support Vector Regression (SVR) is an SVM technique for regression instances that overcomes overfitting and yields high performance [19]. the dataset (i.e., the classification) into two zones (i.e., clusters), SVR aims to combine the entire dataset into one zone while optimizing the epsilon distance (ε) (small value). Figure 2 is the SVR illustration.

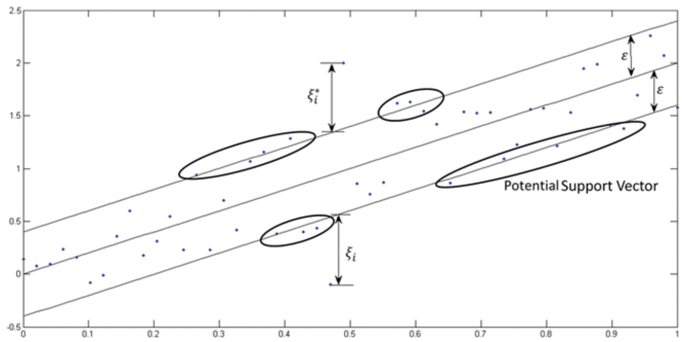

Figure 2 *SVR Illustration [20]*

In Figure 1, a hyperplane (diagonal line in the centre) is surrounded on either side by two lines. It is also clear that there is a gap of between the hyperplane and the two boundary lines. Numerous data points that have been circled represent potential support vectors, which means that they are now potential boundaries.

Finding a hyperplane (dividing line) in the form of a regression function that matches all input data with the minimum error is the goal of the SVR, which also aims to transfer the input vector into a higher dimension [19]. Function can be stated as function in the notion of linear regression (1) [21].

$$f(x) = w^T\varphi(x) + b \qquad (1)$$

Where $\varphi(x)$ is a function that converts x to the feature space with l dimensions, w is the weight vector with l dimension, and b represents bias. The mapping of the input vector in the lower level input space produces a point in the higher dimensional feature space, which is represented by the function of $\varphi(x)$.

The risk function is minimized to estimate the coefficients w and b. Consequently, a minimum $\|w\|$ is required in order to optimize the margin δ, Problem-solving optimization can be expressed as a function (2).

$$min\tfrac{1}{2}\|w\|^2 \qquad (2)$$

with the circumstance, $y_i - w^T\varphi(x_i) - b \leq \varepsilon, for\ i = 1, \dots, l$

$w^T\varphi(x_i) - y_i + b \leq \varepsilon, for\ i = 1, \dots, l.$

Where $\varphi(x_i)$ is the estimated value for i period and y_i is actual value for i period.

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Regulation is referred to as the $\|w\|^2$ factor. A function will become as thin (flat) as possible by minimizing $\|w\|^2$, allowing it to regulate the function capacity. To solve the optimization problem above, which can be expressed as a function (3), all points outside of the margin or limit ε will be penalized [19].

$$min\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{\ell}(\xi_i + \xi_i^*) \quad (3)$$

with the condition, $y_i - w^T\varphi(x_i) - b - \xi_i \leq \varepsilon, \quad i = 1, \dots, l$

$w^T\varphi(x_i) - y_i + b - \xi_i^* \leq \varepsilon, \quad i = 1, \dots, l$

$\xi_i, \xi_i^* \geq 0$

The value of the constant C ($C > 0$) controls how far the mistake deviates from the acceptable limit ε. The objective of the convex linear programming NLP optimization problem is to reduce the quadratic function into a constraint. The Lagrange Multiplier function can be used to overcome this restriction. Function (4) is obtained after going through several mathematical steps in a highly drawn-out and difficult derivation approach.

$$f(x) = \sum_{i=1}^{l}(a_i - a_i^*).(x_i.x) + b \quad (4)$$

Where the test vector is x and the support vector is x_i. Linear issues can be resolved with the aforementioned functions.

The final equation in non-linear problems is function after the values of x_i and x are first translated into a high-dimensional feature space by mapping the vectors x_i and x into the kernel function(5)

$$f(x) = \sum_{i=1}^{l}(a_i - a_i^*).K(x_i.x) + b \quad (5)$$

In resolving non-linear problems with algorithms Support Vector Regression (SVR), then it is used kernel function. In problem solving linear with high dimensional space, that is needs to be done, namely replacing the inner product $(x_i.x_j)$ with kernel functions. The advantages of the use of this kernal function is capable relates to the dimensionless feature space higher without the need for calculations explicit mapping [22]. Support Vector algorithm work regression is determined by the type of kernel function which will be used and parameter settings kernel [23]. Kernel function often used is the Linear Function and Radial Basis Function (RBF) [19].

Table 1 Kernel Function

Kernel	Function
Radial Basis Function	$K(\vec{x}_i, \vec{x}_j) = exp(-\frac{\|\vec{x}_i - \vec{x}_j\|^2}{2\sigma^2})$
Polynomial Function	$K(\vec{x}_i, \vec{x}_j) = \left((\vec{x}_i, \vec{x}_j) + c\right)^d$

2.3. Root Mean Squared Error (RMSE)

Root Mean Square Error (RMSE) is algorithms that are often used to assess machine learning algorithms or machines learning, including distant algorithms more sophisticated than linear regression [24]. The RMSE value is used for vary the performance of the model

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in a period calibration with validation period as well is used for performance comparisons between individual model with prediction model [3].

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Y_i - \dot{Y}_i)^2}{n}} \quad (6)$$

Where n is the number of observed data, Y_i is the number of actual data, $\dot{Y}_i$ is the number of output (predict/forecast) data, and so on.

3. RESULT AND ANALYSIS

The outcomes of the SVR analysis, which uses input from the AR and ARMA models to anticipate and make predictions, will be covered in this section. The kernels to be used are Radial Basis Function (RBF) and Linear Function, which will be seen the performance or measure of the goodness of fit for model with the Root Mean Squared Error (RMSE).

For small tables, please place it within a column and bigger table be placed in a text frame spanning to both columns. Use the Table facility available within the MSWord. The font in the row header should be bold and you can use the style available from the style palette.

3.1. Plot of Data

At this section, plot of data is checked using a line chart, an overview of the data plot used in this study can be seen in Figure 3. Data is electricity load realization data (Kilowatt) for March 20, 2019 to January 24, 2021 as a stationary data, which moves up and down.

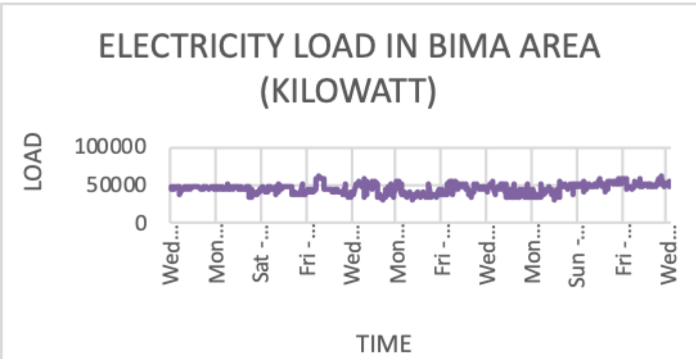

***Figure 3** Actual Data Pattern*

3.2. Input AR and ARMA Model

Input of AR and ARMA model are used for SVR input. At Figure 4 is plot of ACF for AR model, and Figure 4 is plot of ACF ARMA model.

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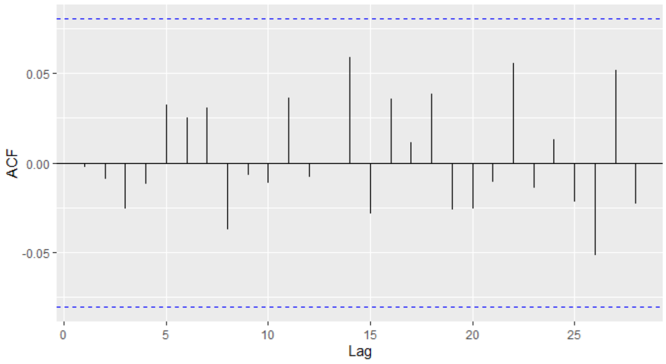

Figure 4 *Plot ACF of AR Model*

Based on Figure 4, AR model is AR(3).

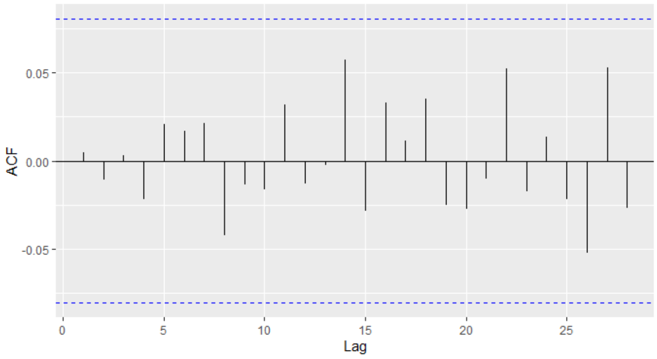

Figure 5 *Plot ACF of ARMA Model*

Based on Figure 5, ARMA model is AR(1) and MA(1).

3.3. Support Vector Regression (SVR) Models of Input AR Model

In this case, the tuning method is used to parameter estimation of SVR model using RBF and Linear Function Kernel.

3.3.1. Radial Basis Function (RBF) Kernel

RBF kernels generate best parameter values:

- $Cost\ (C) = 1.258925$
- $Gamma\ (\gamma) = 1$
- $Epsilon\ (\varepsilon) = 0.1$
- $Sigma\ (\sigma) = 1094.644$

$$\beta_0 = -0.0863293$$

$$(\vec{x}_i, \vec{x}_j) = \exp(-\frac{\| \vec{x}_i - \vec{x}_j \|^2}{2\sigma^2})$$

$$K(\vec{x}_i, \vec{x}_j) = \exp(-\frac{\| \vec{x}_i - \vec{x}_j \|^2}{2(1094.644^2)})$$

$$f(x) = -0.0863293(\exp(-\frac{\|\vec{x}_i - \vec{x}_j\|^2}{2(1094.644^2)}))$$

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3.3.2. Linear Function Kernel

Linear kernels generate best parameter values:

- $Cost\ (C) = 1.258925$
- $Gamma\ (\gamma) = 0.125$
- $Epsilon\ (\varepsilon) = 0.1$

$$\beta_0 = -0.01794735$$
$$K(\vec{x}_i, \vec{x}_j) = (\vec{x}_i, \vec{x}_j)$$
$$f(x) = -0.01794735(\vec{x}_i, \vec{x}_j)$$

3.3.3. Root Mean Squared Error (RMSE)

In Table 2, the Radial Basis Function and the Linear Function kernels were selected as the two measures of the goodness of the SVR model for input AR (RBF).

Table 2. RMSE of SVR Model with Input AR

	Kernel	RMSE
Training	Radial Basis Function	3830.074
	Linear Function	4357.344
Testing	Radial Basis Function	3527.686
	Linear Function	3252.982

According to Table 2, the RBF for testing data is 3527.686, while the minimum RMSE value for the linear function kernel is 3252.982.

3.4. Support Vector Regression (SVR) Models of Input ARMA Model

3.4.1. Radial basis function (rbf) kernel

RBF kernels generate best parameter values:

- $Cost\ (C) = 12.58925$
- $Gamma\ (\gamma) = 0.125$
- $Epsilon\ (\varepsilon) = 0.1$
- $Sigma\ (\sigma) = 77334.08$

$$\beta_0 = -0.340089$$
$$(\vec{x}_i, \vec{x}_j) = \exp(-\frac{\| \vec{x}_i - \vec{x}_j \|^2}{2\sigma^2})$$
$$K(\vec{x}_i, \vec{x}_j) = \exp(-\frac{\| \vec{x}_i - \vec{x}_j \|^2}{2(77334.08^2)})$$
$$f(x) = -0.340089(\exp(-\frac{\|\vec{x}_i - \vec{x}_j\|^2}{2(77334.08^2)}))$$

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3.4.2. Linear function kernel

Linear kernels generate best parameter values:

- $Cost\ (C) = 1.258925$
- $Gamma\ (\gamma) = 0.125$
- $Epsilon\ (\varepsilon) = 0.1$

$$\beta_0 = -0.01815534$$
$$K(\vec{x}_i, \vec{x}_j) = (\vec{x}_i, \vec{x}_j)$$
$$f(x) = -0.01815534(\vec{x}_i, \vec{x}_j)$$

3.4.3. Root mean squared error (RMSE)

Two kernels, the linear function and the radial basis function, were selected for the input ARMA in Table 3, and the RMSE is a measure of the goodness of the SVR model for those two kernels (RBF).

Table 3. RMSE of SVR Model with input ARMA

	Kernel	RMSE
Training	Radial Basis Function	371.5793
	Linear Function	269.8345
Testing	Radial Basis Function	407.4982
	Linear Function	251.8344

According to Table 3, the testing data's RBF has a value of 407.4982 and the testing data's linear function kernel has a minimal RMSE value of 251.8344.

3.5. Forecast

Figures 6 and 7 shows the outcomes of SVR forecasting on test data using the linear kernel function. It is evident that there is a pattern that tends to be consistent between the predicting findings and the testing / real data. The model that is created from the training data is tested using testing data. Based on how closely the outcomes of the goodness of the models match up, training and testing can determine whether certain traits are similar to or suitable for each other. Forecasting is carried out for 85 times, from January 25 to April 18, 2021.

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3.5.1. SVR Models of Input AR Model

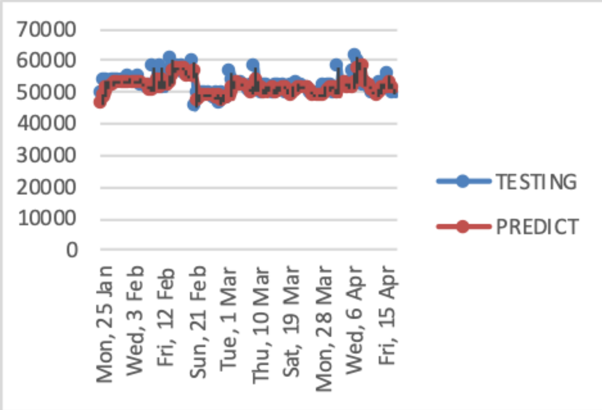

Figure 6 *Forecast SVR of Input AR*

The predicting results and testing data of the input AR are plotted in Figure 6 in a manner that resembles one another, with the lines appearing to move in the same direction. Based on how closely the outcomes of the goodness of the models match up, training and testing can determine whether certain traits are similar to or suitable for each other. Between January 25 and April 18, 2021, forecasting is done 85 times.

3.5.2. SVR Models of Input ARMA Model

The forecasting results and testing data of the input ARMA are plotted together in Figure 7 so that it is clear that the lines on the plot coincide. Based on how closely the outcomes of the goodness of the models match up, training and testing can determine whether certain traits are similar to or suitable for each other. Between January 25 and April 18, 2021, forecasting is done 85 times.

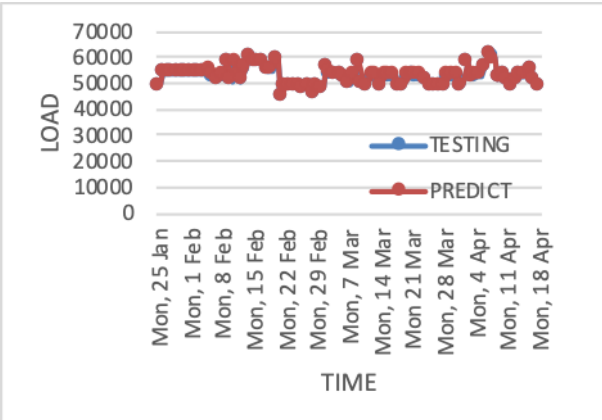

Figure 7 *Forecast SVR of Input ARMA*

4. CONCLUSION

Following the analysis, the following conclusions may be drawn:

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1. The linear kernel function had the lower RMSE value when comparing the RMSE values of the linear kernel function with the RBF.
2. Based on the calculated RMSE value, it can be concluded that the SVR model is straightforward for the realization of electricity load in the Bima region since the linear kernel exhibits the best performance and forecast accuracy.

5. AUTHORS' CONTRIBUTIONS

The author's contribution to this paper is to do all aspects of writing this paper, starting from conceived and design the analysis, collected the data, define analysis tools, perform the analysis, then to write the paper.

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