Inferring Construction Activities from Structural Responses Using Support Vector Machines

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Abstract –

On-site data collection during construction activities help in evaluating productivity rates and preparing more accurate schedules. One of the challenges here is in collecting data automatically such that activity start times and durations can be computed reliably. This paper proposes a methodology to infer construction activities that are being performed on site using the structural responses collected from construction equipments. This methodology is applied to the case of a launching girder, an equipment used in the construction of viaducts in metro rail projects. There are four stages involved in the construction of a viaduct; Auto launching, Segment lifting, Post tensioning and Span lowering. Strain values from the launching girder are used to predict the stages of construction using machine learning techniques. Support Vector Machines are used to classify the strain data into one of the four classes corresponding the stage of construction. Data from a typical construction cycle is used for training. Using the model generated by the training data, subsequent activities can be inferred.

Keywords –

Support Vector Machines, Machine Learning, Automated Data Collection, Construction Progress Monitoring

1 Introduction and Background

Construction activities are inherently complex with the large extend of uncertainties involved in site conditions. Well prepared construction schedule is essential for successful implementation of any construction project. Problems caused by an optimistically biased baseline schedule of a construction project can be rectified by real time accurate construction monitoring. Most of the time, precise monitoring of construction activities are highly challenging. Control of project performance based on manually collected data is a strenuous task. Depending upon the level and accuracy of data required, the cost and effort associated with manual data collection and interpretation of the same for useful information are high [1]. Automated data collection techniques such as barcode [2], Radio Frequency Identification [3], Ultra wide band [4], Global Positioning System [5], imaging [6], LIDAR [7] etc. provide reliable data about on site construction progress. Automated data collection methods generate more accurate and integrated control information less expensively. However, the effectiveness of each mode of automated data collection is highly dependent on the type of construction activities involved. Lack of mobility is one of the major drawbacks of currently existing automated data collection techniques. Major project control decisions are usually delayed due to lack of real time progress monitoring or lag in reporting and interpretation of existing progress data. These problems are addressed by integrating the progress monitoring system with main equipment involved in the construction activity.

Sacks et al. proposed a system which use automatically collected data from a central construction equipment for real time progress monitoring which help in better project performance control [8]. The monitoring system consists of a decision rule processor which uses a knowledge base, as well as data from the Building Project Model and a monitoring 'black box' installed on the equipment. The construction equipment selected by Sacks et al. is a tower crane which is used for lifting majority of materials used in construction. Navon and Shpatnitsky monitored an earth moving equipment for automated progress monitoring of road construction [9]. They developed a monitoring and control model which uses location of the equipment and time of measurement collected, using GPS technology as input data.

Depending upon the type of construction, the central equipment to be selected for automated progress monitoring varies. Soman et al. measured structural responses from a launching girder (LG), an equipment used for construction of viaducts to monitor progress of construction [10,11]. Auto launching, Segment lifting, Post tensioning and Span lowering are the four stages involved in the segmental construction of a metro rail viaduct. Structural response data from the equipment is acquired through a strain based wireless sensing system. Model based system identification methodologies were then used to find out the state of the construction process to monitor the progress [11]. Three different algorithms were evaluated in this work. The first algorithm used a conventional system identification methodology based on a population of models that represents various possible states of the structure. This approach could not accurately identify the stages of construction. A modified system identification methodology which uses domain specific knowledge in the form of possible sequences of construction activities provided the best results. While this approach has been proved to be successful, there is high computational and cognitive complexity involved. Thousands of models need to be created and simulated using finite element analysis software. Model free approaches using machine learning techniques do not have this drawback. These methods do not require models of physical behaviour and are entirely data driven.

Machine learning techniques use data to enhance the performance of software [12]. Some of the major applications of machine learning include device control, recognising biometric parameters, robotics etc. With recent advances, machine learning has entered into almost all industry including construction. Tixier et al used machine learning models Stochastic Gradient Tree Boosting (SGTB) and Random Forest (RF) to predict injuries in construction industry [13]. This study has given dependable probabilistic forecasts of likely outcomes of occurrence of an accident. Akhavian and Amir used machine leaning methodologies to identify and classify activities of construction workers from the data collected using sensors embedded in smart phones [14]. Machine learning techniques are extensively used in structural health monitoring [15] as well as durability and service life assessment of structures [16].

A support vector machine (SVM) is a machine learning technique that has been found to be successful in solving pattern recognition problems [17]. SVM can be used for supervised learning tasks like regression and classification [12]. It has found wide applications in various fields of construction industry. Complex problems such as contractor prequalification can be successfully solved with decision support framework based on SVM [18]. Wauters and Vanhoucke showed that SVM regression model delivers better project control forecasting results than the presently available Earned Value and Earned Schedule methods [19]. Evolutionary Support Vector Machine Inference Model (ESIM) is developed by combining SVM and fast messy genetic algorithm (fmGA). ESIM is capable of determining Estimate at Completion (EAC) of a project [20], identifies the critical parameters that influence the success of a project [21] and acts as a intelligent decision support system for effective construction project management [22]. SVM techniques are extensively used in areas which demand attention to details and patterns, handling of huge amount of data, precise analysis and prediction of future demands. Some of those applications include selection of materials [23], prediction of demand of equipments [24] and working posture analysis of labours [25]. However, inferring construction activities for progress monitoring using predictive analysis by support vector machines classification has not been explored yet.

This paper aims to infer the construction activities of the metro rail viaduct from the structural responses collected from the launching girder using SVM classification.

2 Support Vector Classification

In a simple binary classification problem, the data points are categorised into two classes labelled as positive or negative. The user supplies the training data consisting of values of attributes and label of each of the data point. The learning task is to determine the function that separates the data points into classes. Figure 1 shows a binary classification in which data points consisting of two variables are separated by a straight line. Here, the decision boundary (also known as the classifier or the discriminant) is linear. Decision boundary will be a hyperplane when a linear function divides the classes in multiple dimensions as shown in Figure 2. Equation of a hyperplane is given below [12].

$$f(x) = w_1 x_1 + w_2 x_2 + w_3 x_3 + \cdots + b = 0 \qquad (1)$$

where w_1, w_2, w_3... represent weight factors, x_1, x_2, x_3... stand for input variables and b represents the bias. All the points belonging to one class lie above the hyperplane and those belonging to the other class lie below the hyperplane. The learning algorithm finds the best hyperplane by adjusting the weight factors appropriately. The value of the function f(x) for the first class will be greater than zero and for the second class will be less than or equal to zero.

SVM outputs an optimal hyperplane known as the maximal margin classifier, for a given labelled training data. A good separation is achieved by this hyperplane that has the largest distance to the nearest training data points of any class [12]. Figure 2 shows a maximal margin hyperplane. From the decision boundary, nearest negative data points and positive data points are equally distributed.

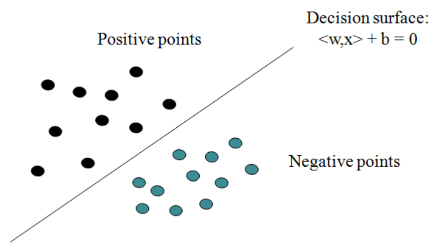

Figure 1. Binary Classification of data points with straight line as decision boundary

When we label the training data as $\{x_i,y_i\}$, i = 1, ... , l, $y_i \in \{-1,1\}$, $x_i \in R^d$, the equation of the hyperplane can be written as given in (2). The solution is obtained by Kuhn - Tucker conditions as given in (3). $\alpha_i, i = 1, \ldots, l,$ stand for positive Lagrange multipliers introduced.

$$f(x) = sgn((w.x) + b) \tag{2}$$
$$w = \sum_{i=1}^{l} \alpha_i y_i x_i \tag{3}$$

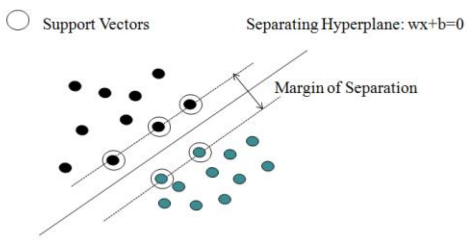

Figure 2. Classification of data points with linear separating hyperplane

We will not get a feasible solution, when we apply the above mathematical model to non-separable data. Therefore, positive slack variables are introduced in the constraints with an additional cost. Larger the value of the newly introduced parameter C in the constraint, higher the penalty to errors [17].

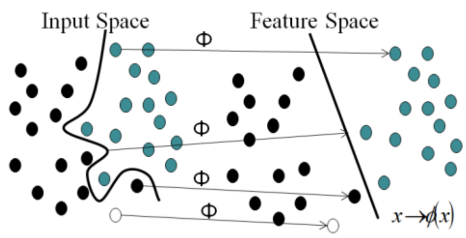

Figure 3. Nonlinear classification of data points with radial basis function

The decision function (2) can also be written as (4). In nonlinear classification, first we embed the data into a high dimensional feature space by a map ϕ and then separate the classes using a maximum margin hyperplane as shown in Figure 3. By suitably introducing a kernel function, K as in (5), the decision function will take the form (6). All concepts of linear classification cases are applicable to nonlinear classification cases. By using kernel function as in (7) the support vector algorithm develops radial basis function (RBF) classifier [26]. Here, σ is the width of the Gaussian kernel.

$$f(x) = sgn\left(\sum_{i=1}^{l} y_i \alpha_i . (x.x_i) + b\right) \tag{4}$$
$$K(x, x_i) = (\phi(x).\phi(x_i)) \tag{5}$$
$$f(x) = sgn\left(\sum_{i=1}^{l} y_i \alpha_i . K(x, x_i) + b\right) \tag{6}$$
$$K(x, x_i) = e^{\left(\frac{-\|x - x_i\|^2}{2\sigma^2}\right)} \tag{7}$$

3 Methodology

Strain readings collected from 14 different locations on the launching girder (LG) in the previous study [11] are used in this research. The objective of this research is to determine whether patterns in strain data could be used to infer construction activities using support vector classification.

11,130 strain gauge readings were used, each from 14 locations of the launching girder during the erection of the viaduct which consisted of 26 cycles. One set of strain data was collected every minute during this measurement sequence. The construction activity corresponding to each data point was obtained from the log book. Strain data for one cycle consists of strain values for the operations, auto launching, segment lifting, post tensioning and span lowering. Data for one cycle is used for training the algorithm and the strain data for other 25 cycles were used for prediction. The aim is to test whether the activities are correctly predicted when compared to the entries in the log book. Prediction is done by linear as well as nonlinear SVM classification. RBF is used for nonlinear classification. The error penalty, C is varied from a range of 10 to 50 and width of the Gaussian kernel, σ is varied from 0.1 to 0.5. It is examined whether these parameters affect the accuracy of prediction as explained below:

In each cycle, data for one operation (such as auto-launching) is taken as the set of positive examples and data for all the remaining operations are taken as negative examples. The SVM is trained using this data for one cycle and remaining data is used for prediction. If the recorded data in the log book matches the identified class, it is considered as correct prediction. The percentage of correct predictions is computed. The results of analysis is discussed in next section.

4 Results and Discussion

Prediction results for each operation involved in a cycle using linear SVM classification and nonlinear SVM classification with RBF are given. Percentage of correct values in prediction (P) is plotted against operations that are treated as the positive class during training (Figures 4-8).

Table 1. Effect of C and σ on Percentage of correct predictions (P) of LG operations

Operations	Linear SVM classification	Nonlinear SVM classification with RBF
Auto launching	P increases as C increases.	P decreases as σ increases; remains same for σ = 0.3 and 0.2, then decreases. Change in C value is not having much impact on result.
Segment lifting	P increases as C increases till C= 20, then decreases.	P increases as σ increases. Change in C value is not having much impact on result.
Post tensioning	P increases as C increases till C= 20, then decreases for C= 30, again increases with C. C= 20 gives better results than other higher values.	P increases as σ increases. Initially P increases with C, then decreases. Value of C corresponding to peak P values, changes with σ value.
Span lowering	P increases as C increases till C= 30, then decreases.	P increases as σ increases. P increases as C increases till 20, then decreases.

Auto launching is having highest percentage of correct predictions. Predictions using RBF gives better results in all the cases, meaning that the decision boundary is non-linear. Prediction of auto launching using RBF gives zero misclassifications in all combinations of C and σ except for C = 20 and σ = 0.2. For that combination of parameters 2 misclassifications were obtained with 98.77% of correct values in prediction. Post tensioning is the operation which shows lowest percentage of accuracy in prediction. Figure 9 shows instantaneous variation of strain at sensor location near middle span of the launching girder during each operation in a cycle. From Figure 9, we can observe that pattern of instantaneous variation of strain during post tensioning is similar to that of span lowering. This makes the prediction process difficult. Initial strain variation pattern of auto launching and segment lifting are similar. This might be the case for all the adjacent operations. But segment lifting operation gives much better results compared to post tensioning. This might be due to large number of training data points involved as well as significant difference in pattern of strain variations.

The percentage of correct predictions (P) varies differently with different combinations of C and σ. Effect of each parameter on each of operations in linear SVM classification and nonlinear SVM classification with RBF are summarised in Table 1.

Soman et al used three system identification methodologies for predicting the construction activities from structural responses [10]. Out of that, a modified system identification methodology using domain specific heuristics is found to be most effective. Table 2 compares the prediction results of linear and nonlinear SVM classification with the modified system identification methodology based on heuristics (MSI). SVM classifications give better predictions compared to MSI in terms of percentage of correct values when you compare the best predictions. As discussed earlier, the best prediction results are from nonlinear SVM classification with RBF and for auto launching operation. In medium level prediction results, only nonlinear SVM classification performs better than MSI. But the identified operation is post tensioning instead of segment lifting as in other methods. As you compare the worst prediction results, MSI gives the most accurate results. Here we can observe the influence of the type of operation identified and values of C and σ. In order for the SVM classifications to give best results we need to carefully choose the tuning parameters.

5 Conclusions

The feasibility of using structural responses from an equipment to infer construction activities is studied in this paper. SVM classification using linear and nonlinear kernels are used to classify the strain data collected from site. Error penalty, C and width of the Gaussian kernel, σ are used as tuning parameters for the study.

It is observed that certain operations such as auto launching and segment lifting can be identified accurately with both classification methods. Computer based pattern recognition is found to be essential in clearly identifying these operations which involve minute changes in strain data, which cannot be accurately detected by humans. Certain other operations such as post tensioning cannot be identified with either of the methods.

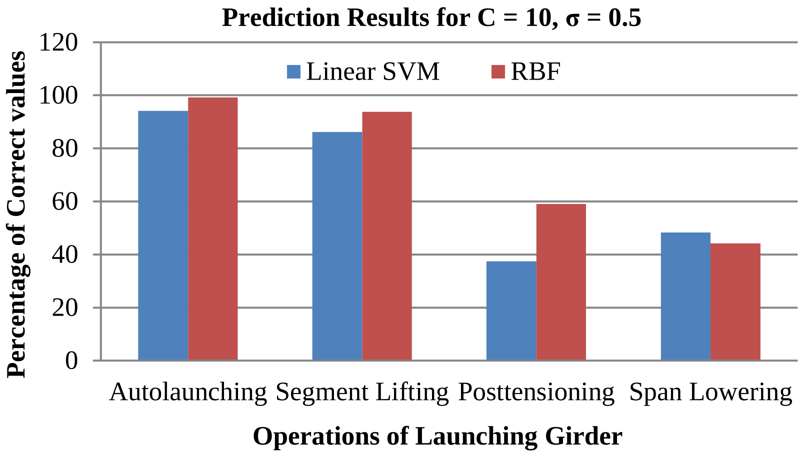

Figure 4. Percentage of correct values in linear and nonlinear SVM classifications. X-axis contains the operations those are treated as the positive class during training. Y-Axis consists of the percentage of correct predictions for this operation.

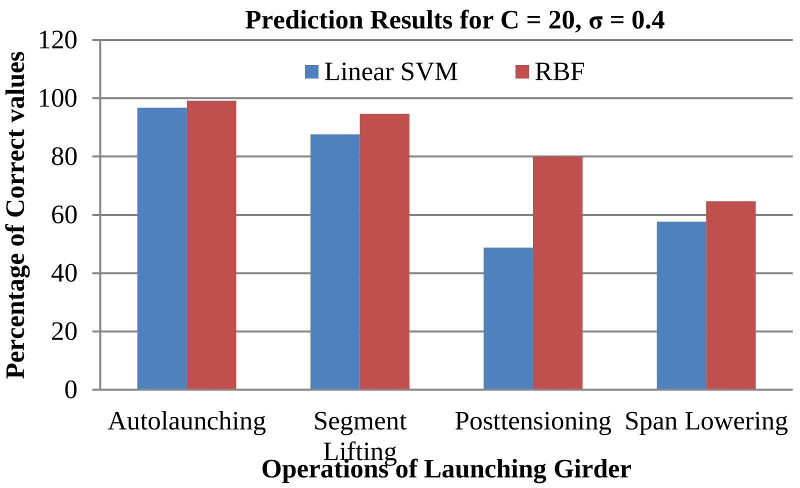

Figure 5. Percentage of correct values in linear and nonlinear SVM classifications.

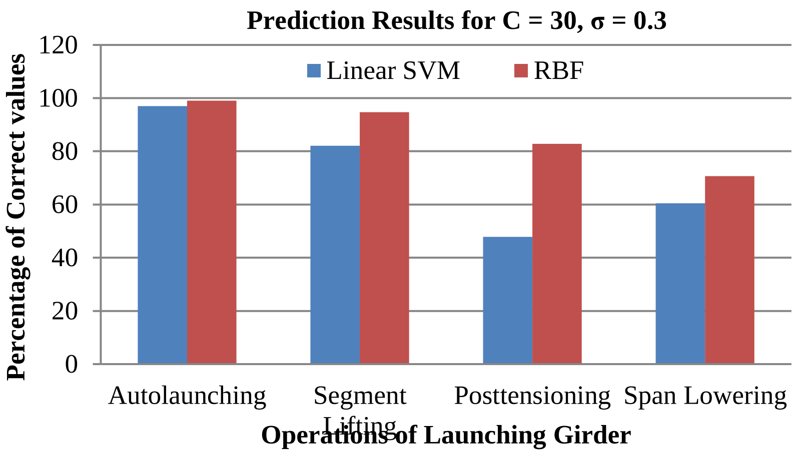

Figure 6. Percentage of correct values in linear and nonlinear SVM classifications.

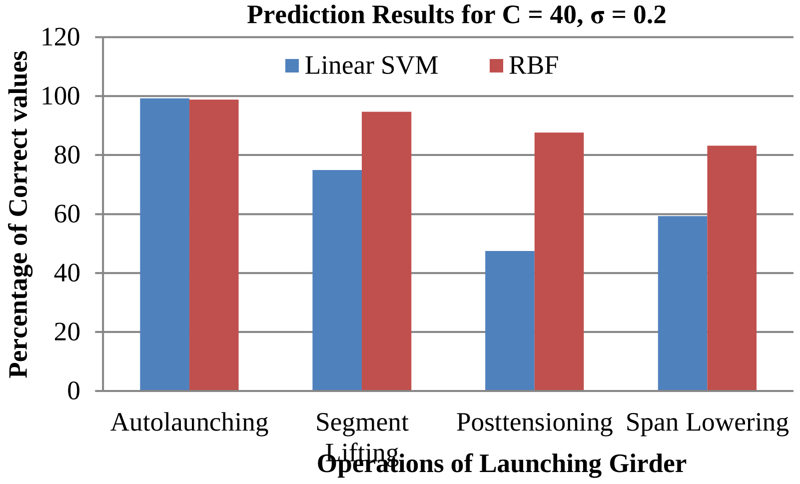

Figure 7. Percentage of correct values in linear and nonlinear SVM classifications.

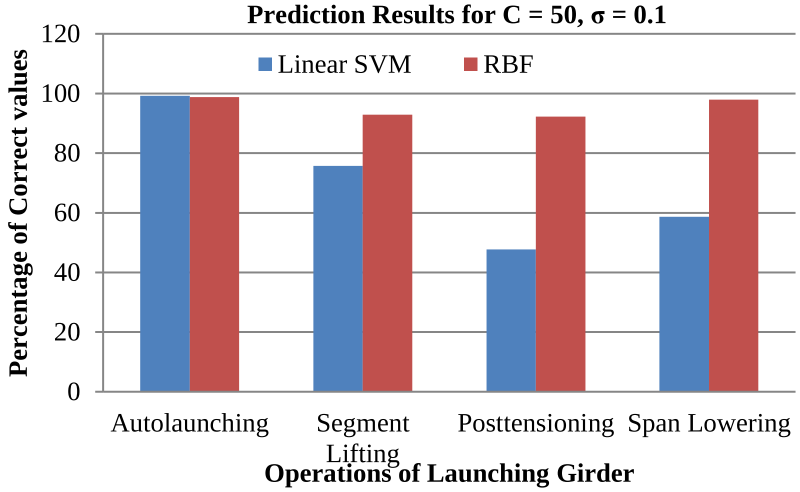

Figure 8. Percentage of correct values in linear and nonlinear SVM classifications.

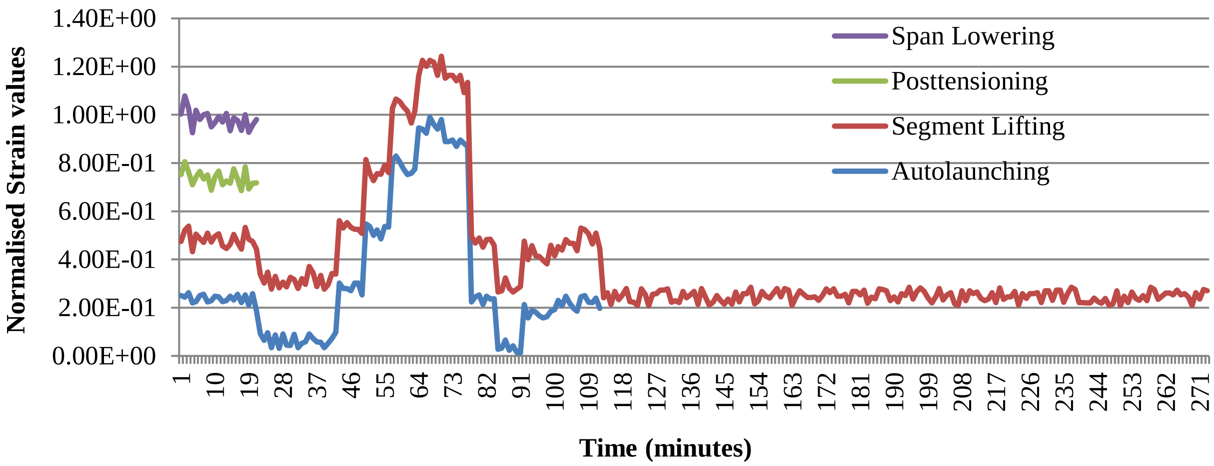

Figure 9. Instantaneous variation of strain at sensor location near middle span of the launching girder

Table 2. Comparison of prediction results of linear and nonlinear SVM classification with modified system identification method based on heuristics [10]

Method of Prediction	Prediction Results					
	Worst Prediction		Medium Prediction		Best Prediction	
	Predicted operation and details of prediction method	Percentage of correct values	Predicted operation and details of prediction method	Percentage of correct values	Predicted operation and details of prediction method	Percentage of correct values
Modified system identification method based on heuristics	Span lowering, with modeling error	79	Segment lifting, without modeling error	81	Auto launching, without modeling error	95
Linear SVM classification	Post tensioning, C = 10	37.39	Segment lifting, C = 40	74.89	Auto launching, C = 50	99.23
Nonlinear SVM classification with RBF	Span lowering, C = 10, σ = 0.5	44.24	Post tensioning, C = 50, σ = 0.2	87.09	Auto launching, C = 20, σ = 0.5	99.23

Strain data alone is not enough in such cases. We might have to include additional sensors like accelerometers to obtain more details about the operations. Strain data from one location is not sufficient to identify operations. Some locations give better strain variations compared to others. Therefore location of sensors should be carefully chosen.

In linear classification, error penalty C is having significant influence. However, accuracy of prediction increases with increase in C only up to certain extend in each operations. There is an optimal value of C for each operations which comes in the range of 20-30.

Nonlinear SVM classification with RBF is mostly governed by width of the Gaussian kernel, σ. Except in auto launching operation, increase in σ value gives better results. Changes in C value for constant value of σ have not much effects on certain operations such as auto launching and segment lifting. Interestingly, both of these operations follow similar strain variation pattern in the initial stage. Post tensioning and span lowering have optimal values of C for a constant σ value. With careful selection of the values of the parameters, SVM classifications can produce better results compared to modified system identification method based on heuristics.

Inferring construction activities from structural responses using support vector machines is possible with optimal values of C and σ determined for each operation. With the help of heuristics and additional types of sensors at best locations, prediction results can be improved.

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