Combining Fuzzy Signature and Rough Sets Approach for Predicting the Minimum Passing Level of Competency Achievement

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ABSTRACT

This paper aims to investigate the important factors that affect the value of the minimum passing level (MPL) of competency achievement and find the best method to predict it. The MPL of competency achievement is the value that represents the minimum passing score of examination related to the competency. Different schools may have a different value of the MPL because the MPL is defined based expert opinion on several uncertainty aspects and conditions at each school. This paper proposes the combination of rough sets and fuzzy signature method to predict the category of the MPL. The rough sets method is applied to reduce unnecessary features for classification and find the important factors to predict the MPL. The fuzzy signature is employed to predict the category of MPL based on the selected features. The method proposed in this paper consists of several stages, namely data collection and pre-processing, features selection, predict the category of the MPL using the combination of rough sets and fuzzy signatures method, and performance evaluation. Fifteen headmasters and sixty teachers of elementary schools participated in the data collection process. Based on the experiment with 203 objects data we achieved 97% accuracy in the prediction of MPL. The proposed method succeeded to identify the important factors on predicting the MPL on the complexity of competency and resource capacity of the school aspect. We obtained the improvement for accuracy of the complexity of competency prediction of 8.5% from the best method in the previous research.

Keywords: Minimum passing level, competency achievement, rough sets, fuzzy signatures.

Mathematics Subject Classification: 68T01

Computing Classification System: I.2.0, I.2.6

1. INTRODUCTION

Currently, all the schools, districts and all states in every country that apply the competency-based education are reforming their education systems to ensure students achieve skills for their college and careers. In the 2016/2017 academic year around 198.410 schools in Indonesia implement the competency-based curriculum (Kemdikbud, 2017). How to measure competency achievement is one of the essential things. Assessment is an evaluation process to appraise the knowledge, the understanding, and the skill's achievement of a student (Authority, 2014). One of the assessment principals on the competency-based curriculum is whether the student overs the minimum passing level of competency achievement or not (Eslami et al., 2017).

In common, students complete some tests in the assessment system. A teacher will assess the competency achievement by evaluating the student's mark with the value of the Minimum Passing Level (MPL). Determination of MPL is vital because it will support the decision making process in defining the student's competency achievement. This process is performed manually by a group of teachers in each school. For several schools, this is a difficult thing to specify MPL's value because experts (teachers) have different opinions in assigning a value to determine it. To support competence-based assessment system, it is required to define MPL's value automatically. The prediction of the complexity of competency automatically has been proposed using the supervised learner's method such as Naïve Bayes, Multilayer Perceptron, SMO, and Ripper. The method achieved the highest accuracy on 90% using SMO and the highest average on 83.87% using the Ripper method (Yuhana et al., 2018). The investigation of the important factors that affect the category of MPL and the best method to predict the MPL are required.

This paper discusses the application of a rough set and fuzzy signature approach to find the important features and to predict the MPL of competency in the student assessment system. This research is part of the development of the competency-based assessment system in Indonesia (Yuhana et al., 2019). Section 2 introduces the concept of MPL of competency achievement, related work, and the proposed method to predict it. Section 3 discusses the results and discussion. Section 4 defines the conclusion.

2. PREDICTING THE MINIMUM PASSING LEVEL METHOD

2.1. The Minimum Passing Level of Competency Achievement

The minimum passing level (MPL) of competency achievement is the value that represents the minimum passing score of examinations related to the competency. In Indonesia, the range value of the MPL is from 0 to 100. Different schools have a different value of the MPL. The MPL is defined based on the resources and the conditions of the school. The factors affect the value of the MPL are Complexity of Competency (Yuhana et al., 2018), Resource Capacity of School, and the Student Intake.

The complexity of competency CoC is classified based on six factors, i.e. human resource skill HRS, student's reasoning ability RA, student's skill CAP, student's creativity CS, time spent by students ST to understand the competency, student's accuracy and reasoning ability AR. Whether, the resource capacity of the school RCS is classified using these five factors, i.e. human resource availability HRA, school facility and infrastructure FI, availability of operational cost of school OCS, availability of school management SM, availability of concern of school stakeholder CSS. The Student Intake SI is defined based on the average score of students in the previous level.

2.2. Related Work

Feature selection removes the number of negligible features in classification rules (Zhang and Yao, 2004). In defining the decision several attributes are less significance and not equally important, then, by reducing irrelevant attributes it will simpler to make the correct decision(Wei, 2009). To deal with real-valued datasets, several researchers utilized the rough sets based approach. The approach can be used to lessen irrelevant features and reduce the complexity of the classification task (Anaraki, 2013; Grzymala-busse, 2005; Zhang and Yao, 2004). The implementation of rough sets for feature selection improved the performance of the classifiers in classifying various datasets (Antony et al., 2016).

Fuzzy sets concept was introduced by L.A. Zadeh to deal with uncertainty data (Zadeh, 1965). Fuzzy logic transforms rules expressed by a human into a mechanized control approach (Mamdani and Assilian, 1975). Many researchers have been utilizing the fuzzy-based method to solve the problems in many domains, especially in education (Chai et al., 2014; Ghorbani and Montazer, 2015; Gisolfi et al., 1992; Jevšček, 2016; N. Yusof et al., 2012; Verdú et al., 2012). The further concept, fuzzy signatures, organizes data into vectors of fuzzy values, each of which can be a further vector. The fuzzy signature can be well used for modeling problems that may be modeled by a hierarchical structure (Kóczy et al., 1999). Fuzzy signature modeling suitable for assessment such building assessment (Bukovics et al., 2018), assessment for SAR (Mendis, 2006). Fuzzy signature is robust under the condition of incomplete data (Mendis, 2006). A fuzzy signature F can be defined as,

$$f : X \to [a_i]_{i=1}^{k}, \text{where } a_i = \begin{cases} [0,1] \text{ ; if leafe} \\ [a_{ij}]_{j=1}^{k_i} \text{ ; } if\ branch \end{cases} \tag{1}$$

Figure 1 shows an example of a fuzzy signature which represents the minimum passing level of competency achievement. MPL condition is given by three aspects, namely CoC, RCS and SI. These aspects further represented by several measured values. As an example, CoC depends on several conditions, namely $HRS, RA, CAP, CS, ST,$ and AR. Also, these measured values are represented by teachers or school headmasters. For example, HRS is given by one of three analysis levels, namely $high, medium,$ or low, according to teachers or school headmasters.

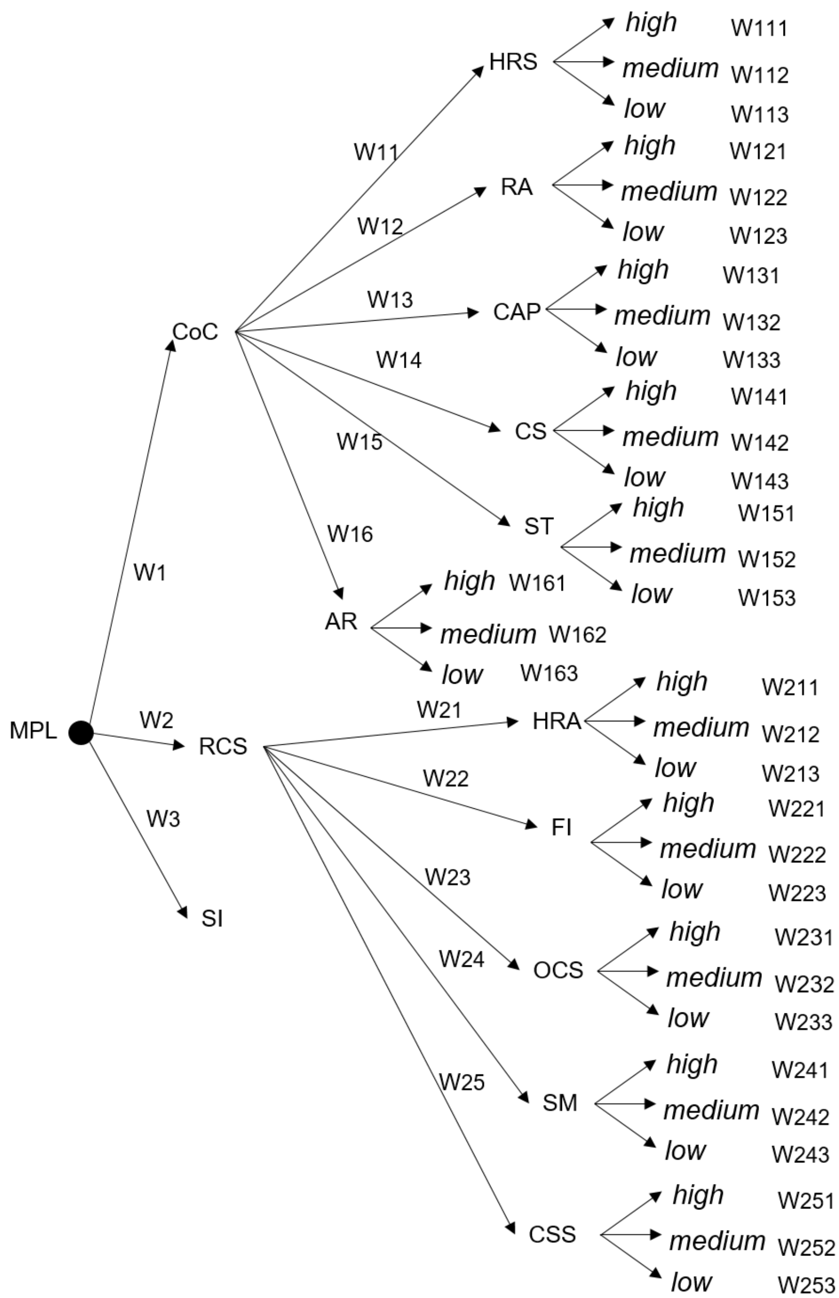

Figure 1. MPL Fuzzy Signature Structure

2.3. Prediction Methods

Figure 2 shows the proposed method to predict the minimum passing level of competency achievement. We follow the established machine learning method and utilize the following steps:

1. Data collection and pre-processing
2. Features selection using rough sets method
    a. Features selection to define the complexity of competency CoC value

   b. Features selection to define the resource capacity of school RCS value
3. Predict the minimum passing level of the competency achievement using a combination of rough sets and fuzzy signature method.
   a. Predict the value of the complexity of competency CoC using the rough sets method
   b. Predict the value of the resource capacity of school RCS using the rough sets method
   c. Predict the minimum passing level of the competency achievement using the fuzzy signature method
4. Performance evaluation

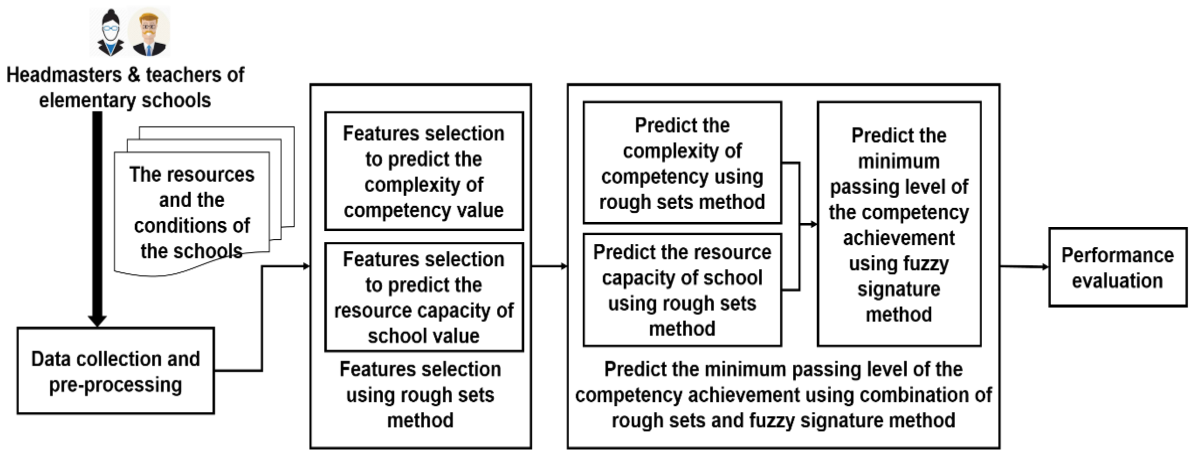

Figure 2. Proposed method

Data collection and pre-processing. In this research, we used primary data collection. Fifteen headmasters and sixty teachers of elementary schools participated in the data collection process. The participants' age range was 23 – 61 years. The participants were selected from the different level of accreditation using a random sampling method. Each participant fills the questionnaire represented the resource and the condition of the school.

The questionnaires were divided into two sections, Questionnaire section A was designed to identify the resource capacity of the school RCS and questionnaire section B was considered to identify the complexity of competency CoC . For each question, the respondents were requested to input the number between 0 and 100. The respondent also required to choose one of three options that represent the conditions in their schools i.e., good, fair, or poor.

Data pre-processing converts the numeric data to be the category of resource or condition, i.e., high, medium, and low, and stores it to the dataset. The dataset contains six condition attributes related to one decision attribute of CoC and five condition attributes related to one decision attribute of RCS . Table 1 shows the list of parameters in the data.

Table 1: List of used parameters

No.	Parameter	Description
1.	HRS	Category of human resource skill in the school. The value represents the status of how the teacher understand the competency must be achieved by the student and how the teacher creative and innovative in implementing learning
2.	RA	Category of students' reasoning ability in the school
3.	CAP	Category of students' capability at applying the concept
4.	CS	Category of the carefulness, creativity, and innovation of the students in the completion of the task or job
5.	ST	Category time spent to make student achieve the competency
6.	AR	Category of the student's accuracy and reasoning ability
7.	CoC	Category of the complexity of competency
8.	HRA	Category of human resource availability
9.	FI	Category of the facility of infrastructure
10.	OCS	Category of the availability of operational cost for the school
11.	SM	Category of the availability of school management
12.	CSS	Category of the concern of school stakeholder
13.	RCS	Category of resource capacity of school
14.	SI	Category of the student intake
15.	MPL	Minimum Passing Level of competency achievement

Features selection using the rough set method. This research used the rough set method to select the features for predicting CoC value and RCS value. Let us consider a decision table including a finite universe of objects U evaluated on a finite set of condition attributes $A = \{a_1, a_2, a_3, ..., a_n\}$, and on a single decision attribute d. Table 2 represents the examples of the information table to predict CoC. In Table 2 attributes $HRS, RA, CAP, CS, ST,$ and AR can be considered as conditions attributes, whereas the attribute CoC as a decision attribute. H, M, and L value refers to high, medium, and low respectively. More complex (difficult) the competence the lower the value. But the easier the competency then the higher the value. Based on human experts, we found that each value of each factor is defined based on the school's conditions. The CoC is high if one factor is high.

Table 3 represents an example of the information table to predict RCS. Table 3 represents an example of the information table to predict RCS. In Table 3 attribute HRA, FI, OCS, SM and CSS can be considered as conditions attributes, whereas the attribute RCS as a decision attribute. HRA

indicates the condition of the availability of teachers in school. The value of HRA is high if the school has full-time classroom and subject teachers from government employees. The value of HRA is medium if the school has two honorary teachers to help classroom teachers and low if the school has more than two honorary teachers to help classroom teacher.

Table 2: Information table to predict CoC

Object	a_1-HRS	a_2-RA	a_3-CAP	a_4-CS	a_5-ST	a_6-AR	$d-CoC$
E1	H	M	M	M	M	M	H
E2	H	M	M	M	H	H	H
E3	H	M	M	M	M	M	H
E4	H	H	H	M	M	M	H
E5	H	M	M	H	M	M	H
E6	H	H	H	H	H	H	H
E7	M	M	M	M	M	M	M
E7	M	M	M	H	H	M	H
E8	M	M	M	M	M	L	L
E9	M	M	L	M	M	M	L
E10	M	M	M	M	M	L	L
E11	M	M	M	M	M	M	M

School facility (FI) represents the completeness of facilities in the school. The value of FI is high if school facilities such as classroom, library, gym, toilet, laboratory, playground, praying room, school medical room, and storeroom are available in school. The value of FI is medium if only several facilities are available and low if less than three facilities are available.

The rough sets method was applied to CoC dataset to choose relevant features for CoC and RCS. From six attributes in CoC dataset, we found that there are four significant attributes to predict CoC, i.e., $HRS, CAP, CS,$ and AR. From five attributes in RCS dataset, we found that important attributes to predict RCS are $HRA, \mathrm{CSS},$ and SM.

Table 3: Information table to predict RCS

Object	a_1-HRA	a_2-FI	a_3-OCS	a_4-SM	a_5-CSS	$d-RCS$
E1	H	M	M	H	M	H
E2	H	M	H	H	M	H
E3	M	M	M	H	M	H
E4	H	H	H	H	M	H
E5	H	H	H	H	M	H
E6	H	M	H	H	L	M
E7	H	M	H	H	L	M
E8	M	M	M	M	M	M
E9	M	M	M	M	M	M

Predict the minimum passing level of competency achievement. The combination of the rough sets and fuzzy signature method were applied to determine the minimum passing level of competency achievement. Figure 3 shows the model of fuzzy signature and rough sets approach to predict the minimum passing level of competency achievement.

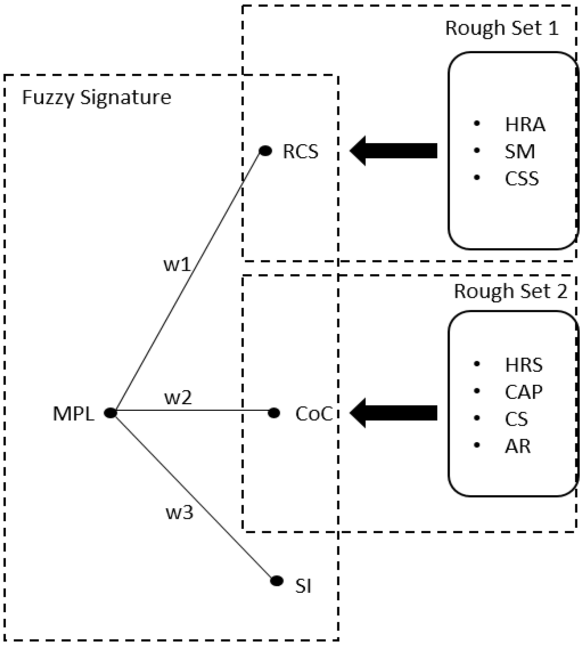

Figure 3. Fuzzy signature and rough sets model for predicting the MPL value

We defined the rough sets rule for determining CoC and RCS . There are six rules from the rough sets method to classify CoC value as follows.

```
Rule 1: IF (HRS = H) THEN (COC = H)
Rule 2: IF (CS = H) THEN (COC = H)
Rule 3: IF (CAP = M) AND (AR = M) THEN (COC = M)
Rule 4: IF (AR = L) THEN (COC = L)
Rule 5: IF (CAP = L) THEN (COC = L)
Rule 6: IF (HRS = M) AND (CS = M) THEN (COC = M)
```

First and second rule define that CoC will be high if HRS is high or CS is high. The third and the six rule explain that CoC will be medium if CAP is medium and AR is medium or if HRS is medium and CS is medium. The fourth and the fifth rule classify CoC to be low if AR is low or CAP is low.

Following rules contain the rough sets rule to classify RCS value.

```
Rule 1: IF (HRA = H) AND (CSS = M) THEN (RCS = H)
Rule 2: IF (SM = H) AND (CSS = M) THEN (RCS = H)
Rule 3: IF (CSS = L) THEN (RCS = M)
Rule 4: IF (HRA = M) AND (SM = M) THEN (RCS = M)
```

The first rule declares if HRA is high and CSS is medium then RCS is high. The second rule classify RCS into high if SM is high and CSS is medium. The third rule states that RCS will be medium if CSS is low. The last rule shows if HRA is medium and SM is medium then RCS to be medium.

The fuzzy signature models the structure of important features for predicting MPL via the hierarchically structured. In this case, weight was given to $RCS, CoC,$ and SI, as based on expert judgment. SI more important than RCS and CoC, and then apply the aggregation using equations, as follows:

$$MPL = w_1 RCS + w_2 CoC + w_3 SI \quad (2)$$

$$w_1 = 0.3; w_2 = 0.3; w_3 = 0.4 \quad (3)$$

Figure 4 shows the membership degree matrix. M_o represents object O's $RCS, CoC,$ and SI.

$$M_o = \begin{array}{c|c|c|c|} & \text{High} & \text{Medium} & \text{Low} \\ \hline RCS & 0.65 & 0.73 & 0.9 \\ \hline CoC & 0.9 & 0.73 & 0.65 \\ \hline SI & 0.9 & 0.73 & 0.65 \\ \hline \end{array}$$

Figure 4. Membership degree matrix

Performance evaluation. We performed two scenarios of experiment to evaluate the performance of proposed method. The first and the second scenario applied rough sets method to predict RCS. The first scenario tried to predict the CoC using supervised learners approach, i.e., Naïve Bayes, MPL, SMO, and Ripper (Yuhana et al. 2018) and then predict the MPL using fuzzy signature. The second scenario predicted the CoC using rough sets method and then predict the MPL using a combination of rough sets and fuzzy signature. The performance will be evaluated using accuracy through the percentage of correctly classified instances and incorrectly classified instances.

3. RESULTS & DISCUSSION

We used 203 objects data from experts, the headmasters and the mathematics teachers of elementary schools, as experimental material. In the first and second scenario, the rough sets method was applied to define the complexity of competency and the resource capacity of the school respectively. To predict the minimum passing level of competency achievement, the first scenario utilized rough sets and the second scenario applied the fuzzy signature method.

Based on the experiments, we found that RCS can be classified with 100% accuracy with 203 objects can be classified correctly. Table 4 shows the confusion matrix in RCS classification. Each column of the matrix represents the instances in a predicted class, while each row represents the instances of an actual class.

Table 4: The confusion matrix of RCS prediction using rough sets

	Predicted		
	Low	**Medium**	**High**
Medium	0	32	0
High	0	0	171
Low	0	0	0

Table 5 shows the confusion matrix in CoC classification, 201 objects from 203 objects can be classified correctly using the rough set method. Table 6 shows the percentage of correctly classify instances and incorrectly classify instances using rough sets and other methods in classifying the CoC. The rough sets approach achieves 98.5% accuracy, better than previous research using Naïve Bayes, Multilayer perceptron, SMO, and Ripper method (Yuhana et al., 2018).

Table 5: The confusion matrix of CoC prediction using rough sets

	Predicted		
	Low	Medium	High
Low	0	3	0
Medium	0	88	0
High	0	0	112

Table 6: Percentage of Correctly Classify Instances (CCI) and Incorrectly Classify Instances (ICI) Of each method in classifying the CoC

Cross-Validation	**Naïve Bayes**		**MLP**		**SMO**		**Ripper**		**Rough Sets**	
	CCI	**ICI**	**CCI**	**ICI**	**CCI**	**ICI**	**CCI**	**ICI**	**CCI**	**ICI**
10 Fold	69.5%	30.5%	84.7%	15.3%	80.3%	19.7%	87.7%	12.3%	98.5%	1.5%
15 Fold	69.5%	30.5%	82.8%	17.2%	79.3%	20.7%	85.7%	14.3%	98.5%	1.5%
20 Fold	71.4%	28.6%	82.8%	17.2%	79.8%	20.2%	83.7%	16.3%	98.5%	1.5%
25 Fold	72.9%	27.1%	82.8%	17.2%	79.8%	20.2%	85.7%	14.3%	98.5%	1.5%
30 Fold	71.4%	28.6%	81.8%	18.2%	79.3%	20.7%	86.2%	13.8%	98.5%	1.5%
Average	70.9%	29.1%	83.0%	17.0%	79.7%	20.3%	85.8%	14.2%	98.5%	1.5%

Table 7 depicts the confusion matrix in MPL prediction. From 203 objects, 7 objects are misclassified. The accuracy of this approach is 97%.

Table 7: Confusion matrix of MPL prediction using fuzzy signature

	Predicted		
	Low	**Medium**	**High**
Low	0	7	0
Medium	0	196	0
High	0	0	0

4. CONCLUSIONS

In this research, we sought to found the important features and the best approach for predicting the MPL. Based on our study, we found that the important features to predict the MPL are $CoC, RCS,$ and SI. Using the rough set method, we obtained that human resource ability HRA, availability of school management SM, and availability of concern of school stakeholder CSS are the most important factors for classifying resource capacity of school RCS. Whether human resource skill HRS, student's creativity CS, student's skill CAP, and student's reasoning ability RA are to be important factors that affect the value of complexity of competency CoC. Based on data from respondents, RCS can be 100% correctly classified using rough set approach. CoC can be classified with 98.5% accuracy using rough set. Combination of fuzzy signature and rough set can be used to predict minimum passing level value with 97% accuracy.

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