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ISM and DEMATEL to determine associations between social media attributes for new product demand forecasting

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***Abstract* — Data from social media is increasingly being utilized to better understand consumer preferences and prospective future demand. In this paper, the Interpretive Structural Modeling (ISM) and the Decision Making Trial and Evaluation Laboratory (DEMATEL) approaches are used to identify the interdependencies and cause-effect between social media attributes centered around better understanding the impact of attributes on product sales. The methodology is demonstrated on a the social media and sales data from a large food and beverage company. Results show that the "followers" and "comments" are interdependent and influenced by the "posts", "impressions" and "videos". The ISM and DEMATEL results are validated with Pearson's correlation coefficient.**

***Keywords*- DEMATEL; ISM; Social media; Variable selection.**

I. Introduction

Social media (SM) platforms such as Facebook, Twitter and Instagram are untapped resources of information that could provide a deeper insight on actual customer demand for products. Some types of products are easily forecastable as they have very solid historical sales on which to build reliable forecasts, however there are many types of products that do not have reliable past sales such as promotional items, multi-generational products, products with intermittent demand or because of major unforeseeable events that changes the demand for the product.

The current management dilemma relative to promotional product demand is made more complex by the lack of direct historical sales information. Data from social media platforms is an underutilized resource for evaluating the influence of user-generated data on product sales and, as a result, forecasting demand for these items. This article uses interpretive structural modelling (ISM) to find the most influencing social media factor and the Decision Making Trial and Evaluation Laboratory (DEMATEL) method to analyze and identify the cause-effect relationship between social media factors. These approaches are validated on a real case of a food and beverage company selling two promotional products each year for an annual special event.

The remainder of the work is organized as follows. Section 2 reviews the existing literature in the use of ISM and DEMATEL in the context of social media analytics, followed by the methodology in section 3. The findings of the methodological technique used in a real-world case study are given and discussed in Section 4. Conclusions and potential areas for more study are offered in the final section.

II. Literature review

Social media networks can be an effective tool for companies to use in the sales of new products. Numerous studies on variable selection have been conducted [1], [2], but none have focused on choosing social media variables to predict the demand for new products. [3] explores the impact of social media sentiment and online user behavior on demand modelling and suggests a method for comparing and contrasting demand models using a variety of social media variables' clusters. In their research, they contrasts other social media variable clusters that are chosen based on their commercial objectives or using machine learning with those that are chosen subjectively (engagement, awareness, consumer metrics and conversion). According to [4], statistical model selection was surpassed by forecast models that used human judgement to choose time-series characteristics. [5] utilize random forest to examine the use of social media variables for operational decision-making and its impact on performance. The authors find that firms that use social media information in their operations have a significantly higher performance than those who do not. They also find that the use of social media information leads to faster and more accurate decision making, improved customer service, and improved supply chain performance. [6] examine the use of the least absolute shrinkage selection operator (LASSO) to select social media variables in forecasting box office revenue for Hollywood films. They compare the performance of models that use social media analysis with models that rely on traditional data sources and find that using social media data can significantly improve the accuracy of box office forecasts, and help to reduce the uncertainty associated with box office predictions, which is particularly important for Hollywood studios that rely on box office revenue to finance their operations.

ISM [7], [8] and DEMATEL [9], [10] are two different methodologies used to analyze the relationship between social media platforms and their impact on decision making. Both of these methodologies can be used to analyze the impact of social media on decision making, but they focus on different aspects of the process. ISM focuses on the spread of information on social media and how it affects decision making, while DEMATEL focuses on the causal relationships between factors that influence decision making.

ISM method is a technique for analyzing complex systems and identifying the relationships between their components. It was first introduced by [11] in the 1970's. The ISM method is based on the idea that complex systems can be represented as a network of interrelated components, and that the relationships between these components can be analyzed to understand the system as a whole. It is widely used in various fields such as decision making, management, engineering, public policy, and operations research to understand and organize complex systems. In recent years, ISM has been used to model a wide range of systems, including organizational structures, supply chains, transportation networks, and political systems. In [12], the authors used an ISM approach to identify the relationships between different factors that contribute to social networking service fatigue. The study surveyed a group of social media users to gather data on their social media usage habits, and then used the ISM approach to identify the factors that contribute to social networking service fatigue, and the relationships between them. The study found that the factors that were most strongly associated with social networking service fatigue were social pressure, addiction, and privacy concerns. The findings of this study suggest that interventions to address social media fatigue should focus on reducing social pressure, addressing addiction, and protecting user privacy. [13] apply an ISM approach to identify the relationships between different factors that contribute to the digitalization of supply chain and identify the technological enablers (e.g., Internet of Things (IoT), blockchain, big data analytics, etc.) for the digitalization of supply chain. By using ISM, the authors identify the key factors that need to be addressed in order to successfully implement digitalization in supply chain. They show that the results of this study could be used to guide the design and implementation of strategies for digitalizing supply chains and achieving greater productivity and performance.

Several extensions and variations have been developed over the years to enhance the ISM method, such as the use of fuzzy logic [14], the integration of other methods like Analytic Network Process (ANP) [15] and Analytic Hierarchy Process (AHP) [16] and the application of ISM in specific domains like sustainability, healthcare, and education. The ISM method is also often used in conjunction with other multicriteria decision analysis techniques [17].

DEMATEL, on the other hand, is a method for analyzing causal relationships in complex systems, particularly in the field of decision making. It is first introduced by the Geneva Research Centre of the Battelle Memorial Institute [18] as a technique for evaluating decision-making problems, and it is commonly used in different fields, which can be seen in the review work of [19], such as management, engineering, and social science to identify the underlying causal relationships between different factors that influence a particular decision or outcome. The method is based on a multi-criteria decision-making approach and uses a combination of statistical and qualitative analysis to identify the most important factors and their causal relationships. In [9], the authors present a hierarchical DEMATEL approach that simplifies complex issues by dealing with numerous sorts of impacts via horizontal decomposition and the presence of hierarchy through vertical decomposition. The proposed technique is used to identify crucial elements in complex systems to both improve the quality of decision-making information and reduce the number of expert opinions. The study described in [20] applies the DEMATEL method to analyze the problem of social media addiction among an university students. They surveyed a group of students to gather data on their social media usage habits, and then used the DEMATEL approach to identify the factors that contribute to addiction, and the relationships between them. The study results showed that the factors that are most strongly associated with social media addiction are emotional dependence, self-esteem, and procrastination. The findings of this study suggest that interventions to address social media addiction should focus on reducing emotional dependence and increasing self-esteem, as well as addressing procrastination. [21] use the DEMATEL technique to investigate the influencing factors for visual perceptions and video communication in social media. The authors show that the results of this study could be used to better understand the factors that influence people's use of visual content and video communication on social media and could help guide the design of interventions to improve the sustainability of social media use.

DEMATEL and ISM are often employed individually to identify hierarchical structure and causal relationships among factors in complex systems with a relatively low computing overhead. However, they may also be coupled based on their shared qualities. In order to further increase the competitiveness of a worldwide supply chain, [22] employed the combined DEMATEL-ISM to evaluate the influencing elements of cross-border e-commerce supply chain resilience (CBSCR). They first develop the CBSCR influencing factor system before applying the fuzzy DEMATEL-ISM approach to examine the comprehensive logical hierarchy, causal relationship, and impact degree among the influencing factors. In order to improve the economic operation of electric vehicle charging stations (EVCS), [23] adopts DEMATEL-ISM approach to identify and analyze its influencing factors. They build the economic operation impact factors system of the EVCS based on the advice of the expert and the relevant data, and they quantitatively analyze the relationship between the different factors. Based on the questionnaire's findings, they show that the influencing elements influence and constrain one another and are not all of equal importance.

Although there are several papers looking at how social media can serve as a source of useful information to understand and predict different phenomena, there is limited research in qualitative methods, such as ISM and DEMATEL, to identify the social media variables that contribute to the sales of products. However, there is still a gap in the literature on the specific methods and metrics that are most effective for forecasting new product success using social media data. Additionally, more research is needed to understand the limitations and potential biases of using social media data in forecasting, as well as the best ways to combine social media data with other forms of market research.

III. Methodology of ISM and DEMATEL

The ISM and the DEMATEL approaches enable to identification of the attributes that most influence the other attributes. Using the DEMATEL approach allows identifying the relationships between different factors that contribute to social media use, and how they influence each other. Whereas

ISM represents the relationships between variables graphically.

A. ISM Method

The ISM method consists of 3 main steps to follow (Figure 1):

1. Create the Self-Structural Interaction Matrix.
2. Establish the Reachability Matrix.
3. Table allowing to breakdown the attributes by levels.

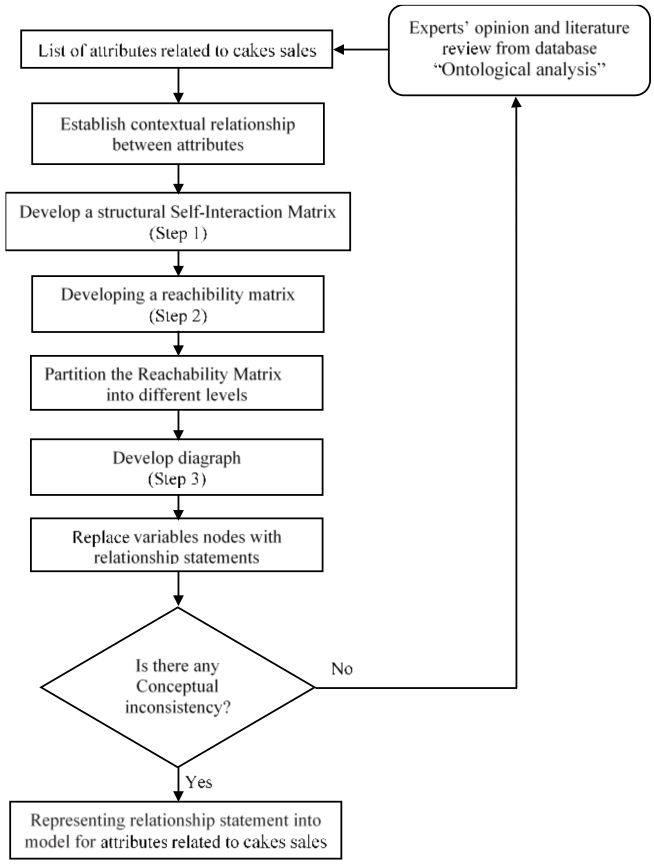

Figure 1. Flowchart of ISM methodology

The first step is to create the Self-Structural Interaction Matrix which is a matrix of size *n* attributes that allows to see the correlation between the different attributes. There are 5 different types of correlation:

- O → attribute without relations
- A → attribute j leads to attribute i
- V → attribute i leads to attribute j
- \- → between same attributes
- X → the attribute i and j will help each other to come true

The second step is to establish the Reachability Matrix to determine the attributes that have a driving power or a dependency power. The transition from the Self-Structural Interaction Matrix to the Reachability Matrix is done with the following algorithm [20]:

- If the entry (i, j) in the SSIM is V, then the entry (i, j) in the reachability matrix becomes 1 and the entry (j, i) becomes 0.
- If entry (i, j) in the SSIM is A, then entry (i, j) in the reachability matrix becomes 0 and entry (j, i) becomes 1.
- If the entry (i, j) in the SSIM is X, then the entry (i, j) in the reachability matrix becomes 1 and the entry (j, i) also becomes 1.
- If the entry (i, j) in the SSIM is O, then the entry (i, j) in the reachability matrix becomes 0 and the entry (j, i) also becomes 0.

The third step is to divide the attributes into tiers in order to identify the most significant elements. To do this, we will examine the reachability set, which corresponds to driving power, and the antecedent set, which corresponds to dependency power, for each attribute, an obtain the intersections between these two columns. The first level will be formed by the greatest common intersections between two attributes. After constructing the first level, the process is restarted to determine the attributes in the second level. The attributes defined in the first level must be deleted in the second iteration, and so on and so forth. The results are a hierarchy of attributes that enable the discernment of the attributes that have the greatest influence on the other attributes.

B. DEMATEL Method

The DEMATEL method is broken down into 6 stages (Figure 2):

1. Initialization of the direct relationship matrix: which allows to determine the influence between each attribute. This influence between attributes is:
   0 - No influence
   1 - Low influence
   2 - Medium influence
   3 - High influence
   4 - Very High influence

   We will then sum each row and keep the highest value (Z).
2. Normalization of the direct relation matrix: which is divided by Z to yield the matrix Y.
3. Estimation of the total relationship matrix:
   - Creation of an identity matrix (matrix I)
   - Calculation of I-Y
   - Do the inverse of the I-Y matrix
   - Final matrix = $Y(\text{inv}(I\text{-}Y))$
   - Sum the rows (R_i) and columns (C_i) of the final matrix
4. Build a direct / indirect relationship matrix T of attributes
   - Add and subtract these sums ($R_i + C_i$ and $R_i - C_i$)
   - When $R_i - C_i$ is negative, the attribute is an effect
   - When $R_i - C_i$ is positive, the attribute is a cause
5. Determining the threshold value
   - Average the values of the final matrix (= threshold value)
   - Identify the values that are greater than this threshold value

6. Formation of the causal digraph
    - Read each line and as soon as the value is greater than the threshold value connected the two attributes by an arrow.
    - Do the same for the columns [21].

IV. Analysis of Social Media Attributes using ISM and DEMATEL

The methodology is demonstrated in a food and beverage company with a large Facebook following of over 400 thousand accounts. This company that supplies B2C to its own restaurants and stores in commercial shopping malls (over 55 locations), and direct customer orders with fresh and frozen products, as well as B2B to supermarkets. The focus is on the new products for an annual special event that lasts for 2-3 weeks. The Facebook data retrieved from the company contains 19,307 datapoints from 23 explanatory variables from January 2017 to July 2019.

Before being able to perform the two methods, it was necessary to reduce the number of social attributes. At first, this database contained about 24 attributes, which for both methods was far too many. For example, for the DEMATEL method, without having reduced the number of attributes, it would have been necessary to determine the influence between each attribute on a 24X24-24 matrix, i.e., approximately 552 elements to be determined. To reduce the number of attributes, an ontological analysis is performed and shown in Figure 3 to group the different attributes into five "attribute types": followers, comments, videos, impressions, and posts.

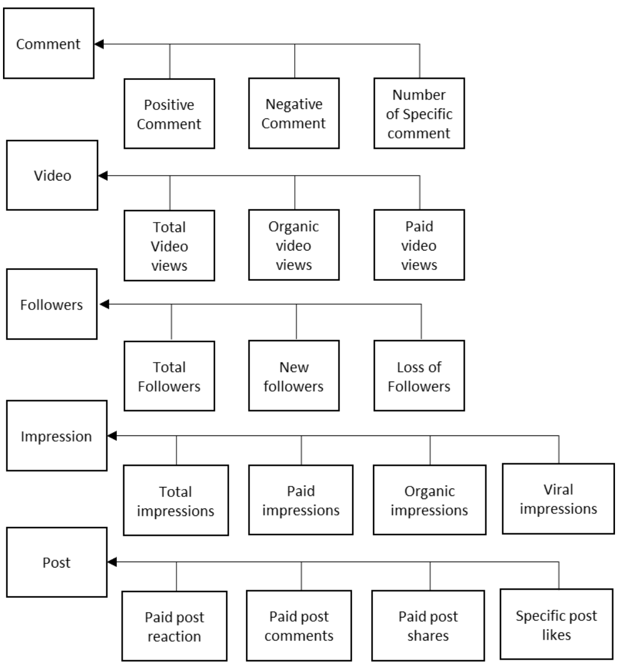

Figure 2. Ontological analysis

The ISM approach is performed on the data and the attributes are classified under two levels as in Figure 4. The graph represents the contextual relationships between attributes. Level 1 consists of the most important attributes according to the ISM approach, which is this case are "comments" and the "followers". These attributes have an impact on each other represented by the arrows. The second level consists of the "posts", "impressions" and "videos" which contribute to increasing the number of "comments" and "followers". These have arrows pointing to the level 1 attributes showing that the attributes of level 2 impact those in level 1.

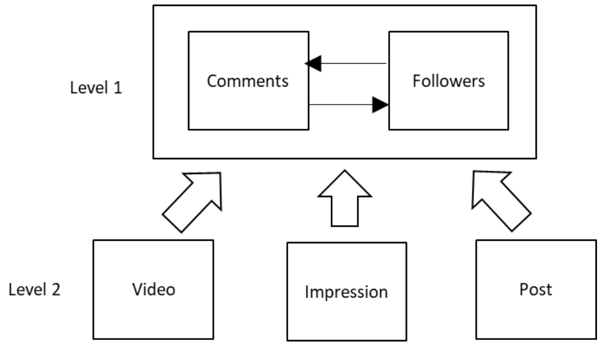

Figure 3. Results of the ISM method

The DEMATEL method enables the identification of the relationships between the attributes. It is firstly necessary to determine the level of influence between all the attributes with different levels using the scale 0 to 4 described in step 1 shown in Table 1. The evaluation is conducted by a decision-maker which is an expert forecaster.

Table 1 Direct Relationship Matrix

	Comments	Video	Followers	Impression	Posts	**SUM (Z)**
Comments	0	1	2	1	1	**5**
Video	4	0	4	1	1	**10**
Followers	1	1	0	1	1	**4**
Impression	1	1	4	0	1	**7**
Posts	4	1	4	1	0	**10**

The direct relation matrix is normalized by dividing by Z to yield the matrix Y (step 2), which is then subtracted from the identity matrix I to generate the final matrix Y(inv(I-Y)).

Final matrix with summed columns (C_i) and rows (R_i) in bold =

$$\begin{array}{c|ccccc|c} & Comments & Video & Likes & Impression & Post & R_i \\ \hline & 1.25 & 0.22 & 0.51 & 0.22 & 0.22 & \mathbf{1.43} \\ & 0.74 & 1.23 & 0.89 & 0.32 & 0.32 & \mathbf{2.49} \\ & 0.31 & 0.20 & 1.31 & 0.20 & 0.20 & \mathbf{1.22} \\ & 0.40 & 0.26 & 0.75 & 1.17 & 0.26 & \mathbf{1.83} \\ & 0.74 & 0.32 & 0.89 & 0.32 & 1.23 & \mathbf{2.49} \\ C_i & \mathbf{2.44} & \mathbf{1.22} & \mathbf{3.36} & \mathbf{1.22} & \mathbf{1.22} & \end{array}$$

The fourth step consists of summing and subtracting the columns (C_i) with the rows (R_i). As mentioned in the methodology, if R_i - C_i is negative, the attribute is considered an effect and if R_i - C_i is positive, the attribute is a cause.

Table 2: Direct / Indirect relationship matrix T for the identification of cause or effect attributes

Attribute	R_i	C_i	$R_i + C_i$	R_i - C_i	Cause or Effect?
Comments	1.43	2.44	3.86	-1.01	Effect
Video	2.49	1.22	3.72	1.27	Cause
Followers	1.22	3.36	4.58	-2.13	Effect
Impression	1.83	1.22	3.06	0.61	Cause
Posts	2.49	1.22	3.72	1.27	Cause

The fifth step is to calculate the threshold value of the matrix *Y* which is taken as the average of the values. The threshold value for our case is 0.38. The values highlighted in bold in matrix *Y* are above the threshold value and indicate the strength of the cause-effect relationship between attributes.

$$Y = \begin{array}{r} \\ \text{Comm.} \\ \text{Video} \\ \text{Follow} \\ \text{Impre.} \\ \text{Posts} \end{array} \begin{array}{c} \begin{array}{ccccc} \text{Comments} & \text{Video} & \text{Follow} & \text{Impres.} & \text{Posts} \end{array} \\ \begin{pmatrix} 0.25 & 0.22 & \mathbf{0.51} & 0.22 & 0.22 \\ \mathbf{0.74} & 0.23 & \mathbf{0.89} & 0.32 & 0.32 \\ 0.31 & 0.20 & 0.31 & 0.20 & 0.20 \\ \mathbf{0.40} & 0.26 & \mathbf{0.75} & 0.17 & 0.26 \\ \mathbf{0.74} & 0.32 & \mathbf{0.89} & 0.32 & 0.23 \end{pmatrix} \end{array}$$

The causal digraph in Figure 5 is build based on the values in matrix *Y* above the threshold value which indicates which attributes are linked, and on the direct / indirect relationship matrix *T* to indicate the direction of causality.

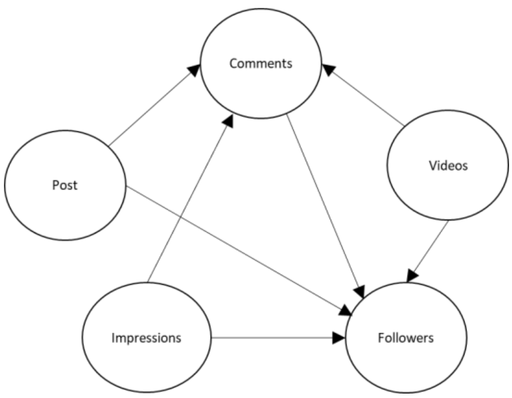

Figure 4. DEMATEL Digraph showing cause-effect relationships amongst social media attributes

As we can see, many arrow are connected to “followers” and “comments”. That’s why, in our case, it is the two attributes indicated as the most important. z

C. *Validation of methodology and discussion of results*

The results from the proposed approached are validated against the Pearson’s correlation coefficient (*r*) between the attributes and sales and the normalised values of *r* shown in Table 3. These values are compared against R_i - C_i from the DEMATEL approach which are also normalised to compare with *r*. The results show that *r* values are aligned with R_i - C_i in that they show a negative correlation for “comments” and “followers” which are the two ‘effect’ attributes and positive correlation for the rest, which are ‘cause’ attributes. Moreover, when normalizing the values in order to compare the strength of their correlations, “followers” has the lowest value, or strongest negative value when comparing *r* with R_i - C_i, followed by “comments”. On the other hand the attributes with the strongest positive values vary between *r* and R_i - C_i, with “impressions” having the highest norm(*r*) but only second highest norm(R_i - C_i).

Table 3: Comparison between correlation coefficient and R_i - C_i from DEMATEL approach

	r	**Norm(*r*)**	**R_i - C_i**	**Norm (R_i - C_i)**
Comments	-0.15	0.2	-1.01	0.3
Video	0.48	0.9	1.27	1.0
Followers	-0.35	0.0	-2.13	0.0
Impressions	0.56	1.0	0.61	0.8
Posts	0.17	0.6	1.27	1.0

The positive or negative sign of *r* is also aligned with the levels of influence using the ISM method with “comments” and “followers” in level 1 (Figure 3), followed by the other attributes in level 2. The comparison with *r* validates the results of DEMATEL and ISM showing that they are both robust methods for determining the levels of influence as well as the cause-effect relationships between social media attributes.

Both ISM and DEMATEL identify the "followers" and "comments" attributes as the most interactive with other attributes, however, these are not two attributes that necessarily result in more sales. In fact, the calculation of *r* shows that these two attributes are negatively correlated to the sales. These two attributes are those which are most influenced by the other attributes, namely “posts”, “impressions” and “videos”. As more social media users view “videos”, or the company content of their feed (“impressions”) or like one of their “posts”, the number of “followers” and “comments” are increased. The ISM and DEMATEL approaches demonstrate the influence of these variables on the number of “comments” and “followers”.

The results from the ISM approach enables managers to determine the interdependencies between social media attributes. In the case study presented in this paper, the “followers” and “comments” are interdependent, but they also depend on the other attributes which impact them. The DEMATEL approach permits to determine the strength of the interdependence between the attributes and the strength with which attributes instigate changes in others. The strength of the associations between the attributes seen in matrix *Y* show that “video” and “posts” have the largest influence on “followers”, followed by “impressions”, and then “comments”. Similarly, “video” and “posts” have the largest influence on “comments” followed by the “impressions”.

The comparison of the DEMATEL results with Pearson’s correlation coefficient validates the approach.

V. Conclusion

Social media information is increasingly being used to understand consumer needs and potential future purchases. This paper uses both ISM and DEMATEL to better understand the relationships between the social media attributes from the Facebook page of a large food and beverage company with the purpose of correctly utilizing them, and potentially avoid multicollinearity, in demand forecasting for new products.

The results from both ISM and DEMATEL approaches identify the "followers" and "comments" social media attributes as interdependent and influenced by the "posts", "impressions", and "videos". The DEMATEL approach also calculates the strength of the associations between the attributes and identifies whether the attributes have more causality on, or have more of an effect by, the other attributes.

A future research direction is to extend the applicability of study to new fields and developing new methodologies to make it more accessible to practitioners by using various advanced techniques such as fuzzy logic, artificial intelligence, and machine learning to improve the accuracy and reliability of the analysis.

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