A Social Account Credibility Evaluation Method Based on Improved Hierarchical Belief Rule Base: Postprint

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Abstract

Social media account credibility assessment is an important component in ensuring the healthy development of online social ecosystems. To address issues such as multi-dimensional credibility assessment indicators for social media accounts and diverse data information uncertainties, a credibility assessment method based on an improved hierarchical belief rule base is proposed. First, the interrelationships among various credibility assessment indicators are analyzed from three perspectives: account attributes, interaction attributes, and content attributes, and based on this, a hierarchical structure for the belief rule base is constructed. Second, adaptive coefficients are introduced into the information conversion function to better describe and handle characteristic differences among indicators. Finally, to compensate for model errors caused by the limitations of expert knowledge, the covariance matrix adaptation evolution strategy with a projection operator is employed to optimize the adaptive coefficients and model parameters. Using Sina Weibo accounts as experimental subjects, the results demonstrate that the proposed method can achieve higher credibility assessment accuracy even with limited data samples.

Full Text

Preamble

A Credibility Evaluation Method for Social Accounts via Improved Hierarchical Belief Rule Base

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Abstract: Social account credibility evaluation is a critical component in ensuring the healthy development of online social ecosystems. To address the challenges posed by multi-dimensional evaluation indicators and diverse forms of data uncertainty in social account credibility assessment, this paper proposes a credibility evaluation method based on an improved hierarchical belief rule base (BRB). First, we analyze the interrelationships among various credibility evaluation indicators from three perspectives—account attributes, communication attributes, and content attributes—and construct a hierarchical belief rule base structure accordingly. Second, we introduce adaptive coefficients into the information transformation function to better characterize and handle the distinctive features among different indicators. Finally, to compensate for model errors arising from the limitations of expert knowledge, we employ a covariance matrix adaptation evolution strategy with projection operators to optimize the adaptive coefficients and model parameters. Using Sina Weibo accounts as experimental subjects, the results demonstrate that the proposed method achieves higher credibility evaluation accuracy even with limited data samples.

Keywords: belief rule base; social accounts; credibility evaluation

0 Introduction

With the continuous development of Internet technology, social media has gradually become the primary means for people to publish, disseminate, and acquire information. While bringing convenience to daily life, the open and shared information dissemination mechanism of social media has also become a potential risk factor in areas such as ideology, information security, and epidemic prevention and control [1,2]. Particularly against the backdrop of deteriorating international situations and frequent global public security events like COVID-19, extremists abroad have exploited social media to spread rumors and phishing links, aiming to commit online fraud, steal state secrets, or even subvert governments. These actions seriously threaten the healthy development of online social ecosystems, cause confusion in public opinion guidance, and affect social stability.

Social accounts are the source of media information publication. Accurately determining account credibility enables relevant authorities to adopt appropriate measures for controlling harmful information. Existing research typically employs various modeling approaches, including machine learning and statistical analysis, to assess social account status [3,4]. For instance, Wang et al. proposed a feature-weighted Bayesian neural network model for microblog account anomaly detection [5], though this approach relies heavily on high-quality training data samples. Hu et al. designed a social account trust model based on rough set theory to distinguish between normal and abnormal account states [1]. Lu et al. developed an account credibility evaluation method combining Bayesian algorithms and analytic hierarchy process, categorizing social accounts into two levels: credible and non-credible [2]. While these methods effectively handle fuzzy uncertainty and probabilistic uncertainty respectively, they lack sufficient quantitative analysis of account credibility. In Liu et al.' s work, social accounts were classified into three categories—normal, compromised, and zombie accounts —using a parallel support vector machine algorithm [4]. Although this method does not require large training samples, it also has shortcomings in uncertainty description and credibility quantification. Credibility evaluation methods based on D-S evidence theory can effectively fuse expert subjective judgments with limited objective data using a belief identification framework to describe information uncertainty, but they struggle with handling conflicting evidence [6,7].

The Belief Rule Base (BRB), developed by Professor Jianbo Yang at the University of Manchester, is a semi-quantitative information evaluation method built upon D-S evidence theory, fuzzy theory, and IF-THEN rules [6,7]. This approach quantifies various forms of uncertainty by introducing a belief framework into traditional IF-THEN rules and handles conflicting evidence through the evidential reasoning (ER) algorithm, which incorporates evidence weights into D-S evidence theory. BRB can effectively integrate expert judgment with sample data for modeling, thereby reducing dependence on high-quality datasets [6,7]. To date, BRB has been widely applied in health status assessment, performance evaluation, and safety assessment of complex engineering systems and large industrial structures [7,8].

Evaluating account credibility involves multi-dimensional indicators such as follower count and comment rate, each with distinct characteristics. Therefore, it is essential to construct a multi-layer evaluation index system that fully incorporates indicator semantics. After constructing the index system, a hierarchical BRB can be employed to evaluate these multi-dimensional, multi-layer indicators. However, in existing hierarchical BRB models, different indicators often share a common information transformation method, and these methods lack adaptability, making it difficult to adequately reflect the specific characteristics of individual indicators. To address this limitation, this paper proposes an Improved Hierarchical Belief Rule Base (IHBRB) method for account credibility evaluation. The main contributions are: (1) proposing credibility evaluation indicators for accounts and constructing a hierarchical BRB evaluation model based on these indicators; and (2) introducing an adaptive indicator information transformation method and implementing adaptive adjustment of relevant parameters through intelligent optimization algorithms.

1 Research Approach

The main research approach for applying IHBRB to social account credibility evaluation is illustrated in Figure 1. The process begins with selecting credibility evaluation indicators and constructing a multi-layer evaluation index system based on these indicators. Next, the IHBRB model is constructed for the index system, and an adaptive information transformation method is proposed. Finally, an optimization model is built to adaptively adjust the key parameters of IHBRB, including belief degrees, attribute weights, rule weights, reference values, and information transformation method parameters. The optimized evaluation model can then be used for social account credibility assessment.

2 Credibility Evaluation Index System Construction

Drawing upon existing research and following the principle of "low cost for indicator information acquisition," we selected indicators that reflect account status from multiple perspectives [1, 9–11].

Account Age, denoted as C_1. This indicator reflects the historical usage of an account. In online social networks, extremists often need to create large numbers of zombie accounts within short timeframes to generate high-intensity public pressure. From this perspective, shorter account age suggests a higher likelihood of being a zombie account and thus lower credibility.

Verification Status, denoted as C_2. This indicator encompasses identity verification, interest verification, Q&A verification, membership verification, etc., reflecting the completeness of account information. On social media, unverified accounts are more common and incur lower costs for producing and disseminating illegal information. Therefore, unverified accounts are considered less credible than verified ones.

Follower Count and Repost/Like/Comment Count, denoted as C_3 and C_4 respectively. These indicators primarily reflect account influence. Generally, accounts with more followers have higher credibility and correspondingly higher repost/like/comment counts. However, for some abnormal accounts that publish rumors, these counts may artificially increase through manipulation by zombie accounts. Consequently, accounts with few followers but high repost/like/comment counts may have low credibility.

Information Originality Rate, denoted as C_5. This indicator is calculated as follows:

$$C_5 = \frac{N_{orig}}{N_{total}}$$

where N_{orig} represents the number of original posts and N_{total} represents the total number of posts. The originality rate can reflect user activity to some extent; accounts with higher originality rates are less likely to be zombie or compromised accounts.

Information Suspicion Rate, denoted as C_6. Whether original or forwarded, information containing abnormal links, random emojis, or meaningless text is considered suspicious. The suspicion rate is calculated as:

$$C_6 = \frac{N_{susp}}{N_{total}}$$

where N_{susp} represents the number of suspicious information items. Higher suspicion rates indicate lower account credibility.

Among these six indicators, account age C_1 and verification status C_2, follower count C_3 and repost/like/comment count C_4, and information originality rate

C_5 and suspicion rate C_6 reflect account credibility from the perspectives of account attributes, communication attributes, and content attributes, respectively. Based on these perspectives, we can further evaluate overall account credibility. Therefore, we construct the hierarchical index system for account credibility evaluation shown in Figure 2, where B represents social account credibility, and B_1, B_2, and B_3 represent credibility of account attributes, communication attributes, and content attributes, respectively.

3.1 IHBRB-Based Credibility Evaluation Framework

Based on the hierarchical index system, we construct the IHBRB-based credibility evaluation model framework shown in Figure 3. BRB-1, BRB-2, and BRB-3 sub-models establish relationships between the three attribute credibilities and their respective indicators, while BRB-4 establishes the nonlinear relationship between the three attribute credibilities and overall account credibility. The IHBRB model employs a bottom-up, layer-by-layer inference approach to obtain final results.

In the IHBRB model, the h-th sub-model is denoted as BRB-h, consisting of a series of belief rules. The k-th rule is described as:

$$R_k : \text{if } X_1^h \text{ is } A_1^k \wedge \cdots \wedge X_{M_h}^h \text{ is } A_{M_h}^k, \text{then } \{(D_1, \beta_{1,k}), \dots, (D_{N_h}, \beta_{N_h,k})\}$$

with rule weight θ_k and attribute weights $\delta_{h,i}$, where X_i^h represents the i-th input indicator of the model (e.g., C_1 and C_2 in BRB-1), A_i^k represents the reference level of X_i^h in the k-th rule, L is the total number of rules, M_h is the number of input indicators, $\wedge$ denotes the logical "AND" relationship, θ_k represents the rule weight, $\delta_{h,i}$ represents the attribute weight of X_i^h, and $\{(D_1, \beta_{1,k}), \dots, (D_{N_h}, \beta_{N_h,k})\}$ represents the belief distribution across different credibility levels in the consequent of the k-th rule, where $\beta_{n,k}$ denotes the support degree for the n-th credibility level D_n, also called the belief degree for D_n.

Input information transformation is a critical step in the IHBRB model, aiming to unify various forms of input information into a belief framework using appropriate transformation methods. This paper proposes a novel adaptive information transformation method based on traditional approaches.

3.2 Adaptive Information Conversion Method

The process of converting input indicator X_i^h into belief distribution form in the IHBRB model can be expressed as:

$$S(X_i^h) = \{(A_{h,i,j}, \alpha_{h,i,j}) | j = 1, 2, \dots, J\}$$

where $\alpha_{h,i,j}$ represents the matching degree of the i-th input indicator relative to the j-th reference level, J is the number of reference levels, $A_{h,i,j}$ represents the attribute reference value, and $f(\cdot)$ represents the transformation function.

In existing studies, traditional BRB models typically employ the transformation method shown in Equation (5) for quantitative inputs:

$$\alpha_{h,i,j} = \frac{|x_i - A_{h,i,j+1}|}{|A_{h,i,j} - A_{h,i,j+1}|}, \quad \text{if } A_{h,i,j} \leq x_i \leq A_{h,i,j+1}$$

where x_i represents the input value of the i-th indicator. As can be seen, this transformation method is linear and struggles to accurately describe the nonlinear relationship between inputs and belief distributions.

To address this limitation, we generalize Equation (5) to enhance its nonlinear descriptive capability. The constructed transformation method is as follows:

$$\alpha_{h,i,j} = \frac{f'(x_i, A_{h,i,j}, A_{h,i,j+1})}{f'(x_i, A_{h,i,j}, A_{h,i,j+1}) + f'(x_i, A_{h,i,j+1}, A_{h,i,j})}$$

where $f'(\cdot)$ represents the improved transformation function:

$$f'(x_i, A_{h,i,j}, A_{h,i,j+1}) = \left[\frac{\max(0, A_{h,i,j+1} - x_i)}{A_{h,i,j+1} - A_{h,i,j}}\right]^s$$

Here, s is an adaptive coefficient that determines the nonlinearity of $f'(\cdot)$, which can be specified by experts or obtained through optimization. To illustrate this, assume $A_{h,i,j} = 0$, $A_{h,i,j+1} = 1$, and $x_i \in [0, 1]$. The output of $f'(\cdot)$ for different values of s is shown in Figure 4. When $0 < s < 1$, $f'(\cdot)$ is a convex function; when $s > 1$, $f'(\cdot)$ is a concave function. Specifically, when $s = 1$, Equation (6) reduces to Equation (5), describing a linear relationship. In practice, assigning different adaptive coefficients to the transformation methods for different indicators enables more accurate and effective information conversion.

3.3 Credibility Assessment Model Inference Method

In the IHBRB model, after input information is converted to belief distributions, rule activation and fusion are required. The output results serve as inputs to the next layer' s sub-model, completing the layer-by-layer inference process. The inference pattern is identical across different sub-models. Taking BRB-h as an example, the main inference steps are:

Step 1 (Rule Activation): After obtaining matching degrees, attribute weights and rule weights are combined to calculate the activation weight of each rule. The activation weight represents the degree to which input information activates a rule, calculated as:

$$w_k = \frac{\theta_k \prod_{i=1}^{M_h} (\alpha_{h,i}^k)^{\bar{\delta}_{h,i}}}{\sum_{l=1}^{L} \theta_l \prod_{i=1}^{M_h} (\alpha_{h,i}^l)^{\bar{\delta}_{h,i}}}$$

where w_k represents the activation weight of the k-th rule (with $0 < w_k \leq 1$), θ_k represents the rule weight, $\alpha_{h,i}^k$ represents the matching degree, and $\bar{\delta}_{h,i}$ represents the normalized relative attribute weight.

Step 2 (Rule Fusion): For activated rules, the evidential reasoning (ER) algorithm fuses the rules. The analytical ER algorithm is expressed as:

$$\hat{\beta}_n = \frac{\prod_{k=1}^{L}(w_k \beta_{n,k} + 1 - w_k \sum_{j=1}^{N_h} \beta_{j,k}) - \prod_{k=1}^{L}(1 - w_k \sum_{j=1}^{N_h} \beta_{j,k})}{\sum_{i=1}^{N_h} \prod_{k=1}^{L}(w_k \beta_{i,k} + 1 - w_k \sum_{j=1}^{N_h} \beta_{j,k}) - (N_h - 1) \prod_{k=1}^{L}(1 - w_k \sum_{j=1}^{N_h} \beta_{j,k})}$$

where $\beta_{n,k}$ represents the belief degree of the k-th rule for the n-th reference level D_n, and $\hat{\beta}_n$ represents the belief degree of the output for the n-th reference level, satisfying $0 \leq \hat{\beta}_n \leq 1$ and $\sum_{n=1}^{N_h} \hat{\beta}_n = 1$.

Step 3 (Assessment Result Output): The evaluation result after inference can be expressed as the following belief distribution:

$$S(y) = \{(D_n, \hat{\beta}_n) | n = 1, 2, \ldots, N_h\}$$

where y represents the output function. The result can be output in utility form as:

$$u(y) = \sum_{n=1}^{N_h} u(D_n) \hat{\beta}_n$$

where $u(D_n)$ represents the utility of reference level D_n.

In IHBRB, $S(y)$ serves as input information for the next layer' s sub-model for further derivation until the final result is generated.

4 Adaptive Optimization of the IHBRB-Based Credibility Evaluation Model

For social account credibility evaluation, existing theoretical methods struggle to establish precise mechanistic models. However, users and experts accumulate experience through long-term use, and some data samples can be obtained through web scraping techniques. The proposed method can comprehensively utilize this information: IHBRB model parameters are initially set by domain experts based on experience and subsequently adjusted using optimization algorithms and data samples to compensate for model errors caused by the limitations of expert knowledge [7].

Existing research on BRB model optimization falls into two main categories [12,13]: one adjusts parameters under certain constraints to minimize error between model output and actual system output; the other introduces structural parameters into the optimization objective to improve modeling accuracy while reducing model complexity. However, neither approach considers the impact of transformation function characteristics on modeling performance during optimization. Therefore, we introduce the adaptive coefficient of the transformation function as an optimizable parameter into the existing optimization objective function. The new optimization objective function and its constraints are constructed as follows:

$$\min \quad \varphi(\theta, \beta, \delta, s) = \frac{1}{T}\sum_{t=1}^{T}(y_t - \hat{y}_t)^2$$

subject to:

$$\begin{aligned}
&0 \le \theta_k \le 1, \quad k = 1, 2, \ldots, L_h, \quad h = 1, 2, \ldots, H \\
&0 \le \beta_{h,n,k} \le 1, \quad n = 1, 2, \ldots, N_h, \quad k = 1, 2, \ldots, L_h, \quad h = 1, 2, \ldots, H \\
&0 \le \delta_{h,i} \le 1, \quad i = 1, 2, \ldots, M_h, \quad h = 1, 2, \ldots, H \\
&s_i > 0, \quad i = 1, 2, \ldots, M \\
&\sum_{n=1}^{N_h} \beta_{h,n,k} = 1, \quad k = 1, 2, \ldots, L_h, \quad h = 1, 2, \ldots, H
\end{aligned}$$

where θ, β, δ, and s are parameter vectors comprising all rule weights, belief degrees, attribute weights, and transformation function adaptive coefficients in IHBRB, respectively; H is the number of sub-models in IHBRB; and φ is the loss function describing the difference between model output and actual system output. In this paper, the loss function is calculated using mean squared error:

$$\varphi = \frac{1}{T}\sum_{t=1}^{T}(y_t - \hat{y}_t)^2$$

where T is the number of outputs, and y_t and $\hat{y}_t$ represent the actual output and model output, respectively.

Existing research has proven that the BRB model is a non-convex model composed of multiple composite functions, which poses challenges for parameter optimization [14]. To improve modeling accuracy, many optimization algorithms have been applied to BRB optimization, such as Differential Evolution (DE), Particle Swarm Optimization (PSO), and Covariance Matrix Adaption Evolution Strategy with Projection (P-CMA-ES) [15-18]. Compared with DE and PSO, P-CMA-ES can generate new solutions using a multivariate normal distribution centered on the expert-determined initial solution, which facilitates full integration of expert initial judgment during model optimization [15]. Additionally, P-CMA-ES demonstrates superior performance in high-dimensional nonlinear optimization, enabling rapid convergence to the global optimum during the search process [15]. The basic flow of P-CMA-ES is shown in Figure 5.

5.1 Case Background

Sina Weibo is a typical popular social media platform in China and an important venue for publishing harmful information such as rumors. Through its long-term operation, it has accumulated vast amounts of account data. This study takes Weibo accounts as research subjects, collecting basic information of 100 accounts registered within 10 years through open data interfaces and general web scraping techniques. By manually analyzing the communication behavior, content publication, and other basic features of these accounts, they were classified into three categories: "completely untrustworthy," "partially trustworthy," and "basically trustworthy." The data for social account credibility evaluation indicators is shown in Figure 6. The results show that various account attributes have certain correlations with account age. However, due to differences in user habits, education levels, and geographic regions, these data cannot intuitively reflect account credibility, necessitating the use of appropriate modeling methods for credibility assessment. This paper employs the proposed IHBRB-based method for case study analysis.

5.2 Case Analysis and Model Construction

When using IHBRB for account credibility evaluation, the first step is to select evaluation indicators and reference levels for credibility.

For account attribute credibility B_1, communication attribute credibility B_2, and content attribute credibility B_3, which are local estimates of social account credibility, their reference levels can be set consistent with those for social account credibility: "completely untrustworthy (U)," "partially trustworthy (P)," and "basically trustworthy (F)," with corresponding reference values of 0, 0.5, and 1, respectively.

For evaluation indicators, reference levels and values can be set as shown in Table 1. Social media account age can be divided into three reference levels: "short (S)," "medium (M)," and "long (L)." Based on experience, the reference value for "short" can be set at 0 years, while "medium" and "long" can be set at 4 and 10 years, respectively. For account verification status, more verifications indicate higher credibility. Reference levels for verification count can be set as "none (NO)," "few (S)," and "many (M)," with reference values of 0, 2, and 5 verifications, respectively. Follower count reference levels can be set as "none (NO)," "few (S)," "normal (N)," and "many (M)," with reference values of 0, 3000, 5000, and 15000 followers, respectively. Repost/like/comment count reference levels can be set as "none (NO)," "few (S)," and "many (M)," with reference values of 0, 50000, and 150000, respectively. Information originality and suspicion rates can be set as "low (L)," "medium (M)," and "high (H)," with reference values of 0%, 50%, and 100%, respectively.

Based on these indicator reference levels and values, initial parameters for each sub-model' s rule base can be specified through expert experience and trend analysis of the data, as shown in Table 2. In the initial IHBRB model, all input weights for the four sub-models are set to 1, all rule weights are set to 1, and the adaptive coefficients for all six input indicator transformation functions are set to 1 (i.e., $s_1 = s_2 = \cdots = s_6 = 1$), making the transformation functions linear.

5.3 Model Optimization and Results Analysis

Due to the limitations of expert knowledge, the initial IHBRB model parameters need to be adjusted using limited data samples. The optimization objective function is determined according to Equations (12) and (13).

In the collected dataset, 50% of the data are randomly selected as the training set, while the entire dataset serves as the test set. For the P-CMA-ES optimization algorithm, the initial parameter vector φ_0 is set to the initial model parameters, the initial covariance matrix C_0 is set to the identity matrix, the initial step size is set to 1, and the number of optimization iterations is set to 200 generations.

The optimized IHBRB model rule weights and belief degrees are shown in Table 3. The optimized indicator weights for each sub-model are 0.75, 1, 0.55, 1, 0.3, 1, 0.93, 0.91, and 1, respectively. The optimized adaptive coefficients for the transformation functions are 1.61, 0.35, 0.59, 1.72, 2.18, and 1.83, respectively. Using both the initial and optimized IHBRB models to evaluate accounts in the test set, the results are shown in Figure 7, demonstrating that the optimized model achieves better credibility evaluation. The mean squared errors of the initial and optimized model outputs are 0.0562 and 0.0028, respectively, representing a 95% improvement in accuracy.

5.4 Comparative Study

To further validate the effectiveness of the proposed method, we conduct comparative studies using IHBRB without adaptive coefficient transformation functions (denoted as IHBRB-1), a neural network model (BPNN), a fuzzy reasoning model (FRM), and a support vector regression model (SVR) to evaluate accounts in the aforementioned dataset. BPNN, FRM, and SVR are commonly used evaluation models: BPNN offers high accuracy and ease of operation; FRM effectively describes and processes fuzzy uncertainty while integrating expert judgment; SVR does not depend on large sample sizes and provides high modeling accuracy. In the comparative experiments, 50% of the data are randomly selected as the training set and the entire dataset as the test set, with 10 rounds of repeated experiments conducted and average results reported.

The experimental results are shown in Figure 8. All models can reflect account credibility to some extent after optimization. Comparing IHBRB with IHBRB-1 results reveals that introducing adaptive coefficients in the transformation function significantly improves evaluation accuracy. FRM shows higher evaluation accuracy for "completely untrustworthy" than for "partially trustworthy" and "basically trustworthy."

For a sample account with 10 years of age, 5 verifications, 37,422 followers, 219,054 repost/like/comments, 97% originality rate, and 3% suspicion rate, expert judgment classifies it as "basically trustworthy." Evaluation results from the five models are: IHBRB outputs belief distribution {0.00, 0.16, 0.84} with credibility utility 0.92; IHBRB-1 outputs {0.05, 0.21, 0.74} with utility 0.84; BPNN outputs credibility 0.81; FRM outputs membership degrees 0.08, 0.33, and 0.59 with utility 0.755; SVR outputs credibility value 0.79. All models classify the account as "basically trustworthy," but IHBRB not only outputs belief degrees across levels but also provides quantified credibility closer to the true value.

To investigate the impact of reduced training samples, we randomly select 40%, 30%, and 20% of data as training sets. The results in Table 4 show that mean squared errors increase for all five models as training set size decreases. However, models like IHBRB, IHBRB-1, and FRM that can determine initial parameters through expert knowledge still achieve good performance with limited optimization data.

To further demonstrate P-CMA-ES effectiveness, we optimize the initial IHBRB model using PSO and DE algorithms under identical dataset and experimental conditions. The mean squared errors of optimized models are shown in Table 5. When the training set ratio is 50%, the three optimization algorithms perform similarly. However, when the ratio decreases to 20%, IHBRB optimized by P-CMA-ES achieves better modeling accuracy.

6 Conclusion

This paper addresses the challenges of multi-dimensional indicators with diverse characteristics and various forms of data uncertainty in social account credibility evaluation. We construct an account credibility evaluation index system from three perspectives—account attributes, communication attributes, and content attributes—and propose an improved hierarchical BRB-based credibility evaluation method. The method employs a hierarchical structure and belief framework to describe inter-indicator relationships and information uncertainty, while introducing adaptive coefficients in the information transformation function to better handle characteristic differences among indicators. Experiments demonstrate that the method can accurately evaluate social account credibility. However, this study has limitations requiring further research, such as integrating deep learning techniques to mine more information for rule base construction and further improving the interpretability of the evaluation process and accuracy of output results.

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Note: Figure translations are in progress. See original paper for figures.