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IDENTIFYING SEVERITY OF MARITIME ACCIDENTS BASED ON WEIGHTED KERNEL DENSITY ESTIMATION

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Abstract. *With the growing volume of maritime logistics, coastal marine traffic environments have become increasingly congested, heightening the risk of maritime accidents. Given their severe human and environmental consequences, identifying risk hotspots and implementing proactive management strategies are essential. Maritime accident severity is not merely a post-hoc score but a practical indicator for prioritizing resources and shaping safety policies. Since real-world damage is strongly influenced by concurrent weather conditions, a valid severity index must incorporate meteorological variables. Meteorological factors such as strong winds, rough seas, strong currents, and good visibility have been widely recognized to substantially influence the severity of maritime accidents in previous studies. Nonetheless, empirical studies that systematically incorporate these factors into the construction of quantitative accident severity indices remain scarce. This study, focusing on South Korean coastal waters, proposes a framework that quantitatively derives optimal severity weights from meteorological data by minimizing prediction error (MSE) in an MLP (Multi-Layer Perceptron) model. Using this refined index, a continuous spatial risk map is generated, and SHAP (Shapley Additive Explanations) analysis identifies key influencing factors. The proposed approach strengthens the explanatory validity of the severity index and supports the transition from reactive analysis to proactive risk.*

Keywords: Maritime accidents, Risk mapping, Accident severity, XAI, SHAP

1. **Introduction.** With the continued growth of global maritime trade, increasingly complex safety challenges are emerging [1]. In South Korea, maritime accident statistics from the Korea Maritime Safety Tribunal [2] show that domestic maritime accidents increased by an average of 6.76% per year from 2010 to 2024. Given that maritime accidents often lead to irreversible ecological, environmental, and economic damage [3], it is crucial to reduce the risk of such incidents through accurate risk analysis [4]. Maritime accidents are influenced by diverse environmental and operational factors [5,6]. In addition, the East Sea, West Sea, and South Sea surrounding the Korean Peninsula each exhibit distinct characteristics in terms of climate conditions, seafloor topography, traffic density, and

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seasonal currents. As a result, it is difficult to directly apply risk prediction models developed in prior international studies to Korean waters. Therefore, there is a need for a risk prediction model and management system tailored to the specific conditions of domestic maritime regions.

Kim et al. [7] proposed a grid-based monitoring framework using South Korea accident data, contributing to the structuring of risk indicators. However, it weighted grids only by accident counts and mean severity, potentially distorting the balance between frequency and severity. Moreover, the grid-based visualization lacked spatial continuity, possibly underestimating risks in unrecorded areas. To address these limitations, several studies have applied Kernel Density Estimation (KDE) to visualizing spatial risk. Yang et al. [8] analyzed maritime accident data from the Fujian coastal area in China using KDE and machine learning models to identify high-risk zones, while Zhang et al. [9] constructed KDE maps by accident type to detect hazardous areas worldwide. However, these studies focused only on accident frequency, overlooking severity. Consequently, regions with few accidents but severe damage may be underestimated. A continuous spatial risk analysis that accounts for both frequency and severity is therefore required.

Numerous studies have been conducted to identify the key factors contributing to maritime accidents. Chang et al. [10] employed a Bayesian network to infer conditional probabilities of accident severity based on discrete meteorological variables such as wind speed, wave height, and current velocity. However, the model relied on predefined probability tables and had limited interpretability for continuous variables. Wang et al. [11] used an ordered logistic regression model to analyze over 1,200 global marine accidents, demonstrating that both vessel-specific factors and meteorological conditions significantly influence accident severity. [12] applied binary logistic regression and Odds Ratios (ORs) to assessing the impact of Blood Alcohol Content (BAC), time of occurrence, and weather conditions on fatal accidents. However, most of the explanatory variables in these studies were treated as categorical or one-unit increment variables, which limited their ability to capture subtle variations or nonlinear relationships across continuous ranges. Previous studies have shown that the Relative Incident Rate (RIR) increases as weather conditions deteriorate [6], and that incorporating meteorological data enhances the accuracy of accident risk prediction [12]. Although the relationship between weather conditions and accident risk is well established, few studies have incorporated these meteorological factors into the construction of quantitative accident severity indices.

To address the limitations of previous studies, this research proposes an integrated spatial analysis and interpretation framework based on a continuous risk map that incorporates accident severity information. The main contributions of this study are as follows.

1) We redefine accident severity by reconstructing the severity formulation proposed in previous studies using meteorological data, which improves the representational accuracy of risk.
2) We generate a continuous spatial risk map by aggregating weighted severity scores of individual accidents at the grid level and applying KDE, enabling the representation of accident frequency and severity in a spatially continuous form.
3) We develop an explainable predictive framework in which an MLP is trained to estimate accident severity and SHAP is applied to identifying key influencing factors at both national and maritime-regional scales, allowing the generation of realistic accident scenarios and enabling interpretable assessments of meteorological impacts.

This approach enables the interpretation of the impact of meteorological factors on maritime accident severity from both global and regional perspectives, contributing to more precise and effective maritime safety management. The remainder of this paper is structured as follows. Section 2 presents the proposed framework. Section 3 discusses the experimental results, and Section 4 concludes with key findings and implications.

2. Proposed Method.

This section proposes a framework for optimizing accident severity weights and, based on the results, constructing a continuous spatial risk map and interpreting the influence of key meteorological factors. The overall methodology consists of four main steps: data integration, optimization of severity scores, spatial risk visualization using weighted KDE, and SHAP-based analysis. The entire procedure is illustrated in Figure 1.

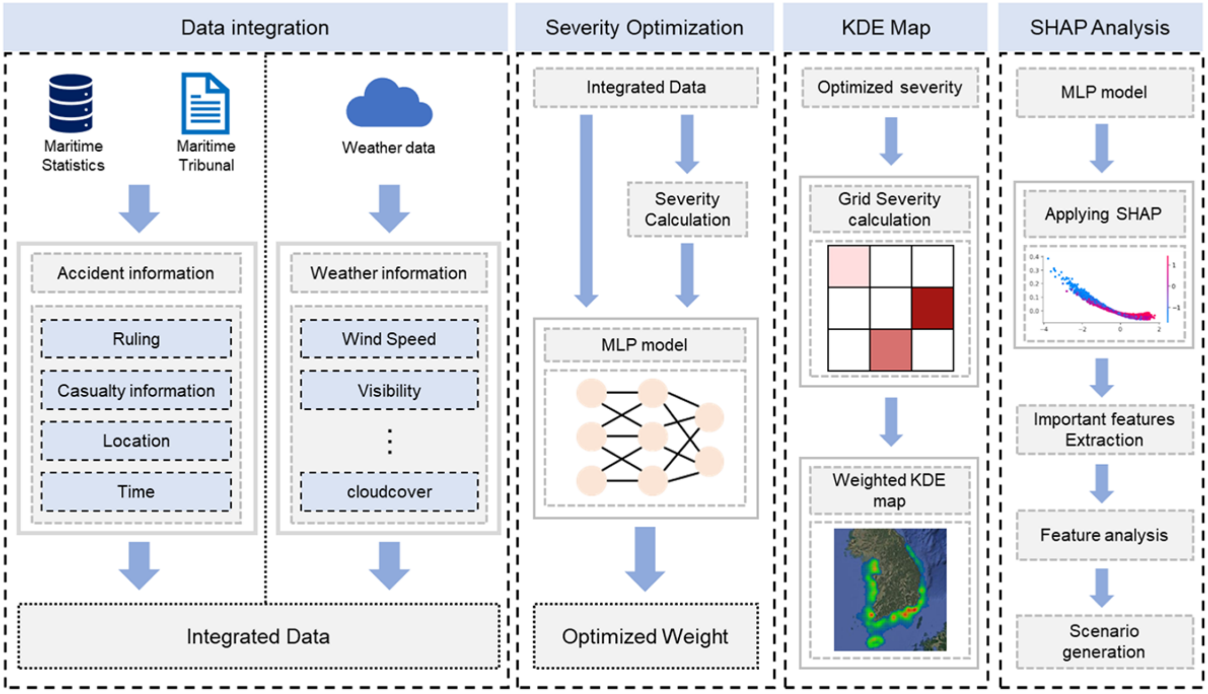


FIGURE 1. Overall framework of the proposed method

2.1. Data.

This study employs a dataset of 19,902 maritime accidents that occurred in South Korean coastal waters from 2018 to 2023. It covers 22 accident types (e.g., collision, flooding, grounding, and capsizing), as shown in Figure 2. The dataset was built by integrating accident reports and statistics from the Korea Maritime Safety Tribunal with meteorological data from Visual Crossing, including accident details (type, location, time, casualties) and weather variables (temperature, humidity, dew point, wind speed, cloud cover, visibility, precipitation, UV index). Accident severity scores were derived from accident and casualty information, and meteorological variables were used to train and interpret the severity prediction model.

2.2. Severity definition and optimization.

Maritime accident severity was evaluated based on the criteria proposed by [7]. The severity score was calculated using Equation (1) from their study, where the accident grade X_1 was assigned as follows: 1.5 points for extremely serious accidents, 1.0 point for serious accidents, and 0.5 points for minor accidents.

$$Severity = \alpha X_1 + (1-\alpha)(X_{death} + X_{missing} + 0.5X_{injury}) \tag{1}$$

In previous studies, the α value was fixed at 0.95 based on the data ratio. While this approach is simple, it assumes that accident severity can be sufficiently explained by classification criteria alone, which may lead to an underestimation of the impact of actual human casualties. To address this limitation, the present study applies a grid search to

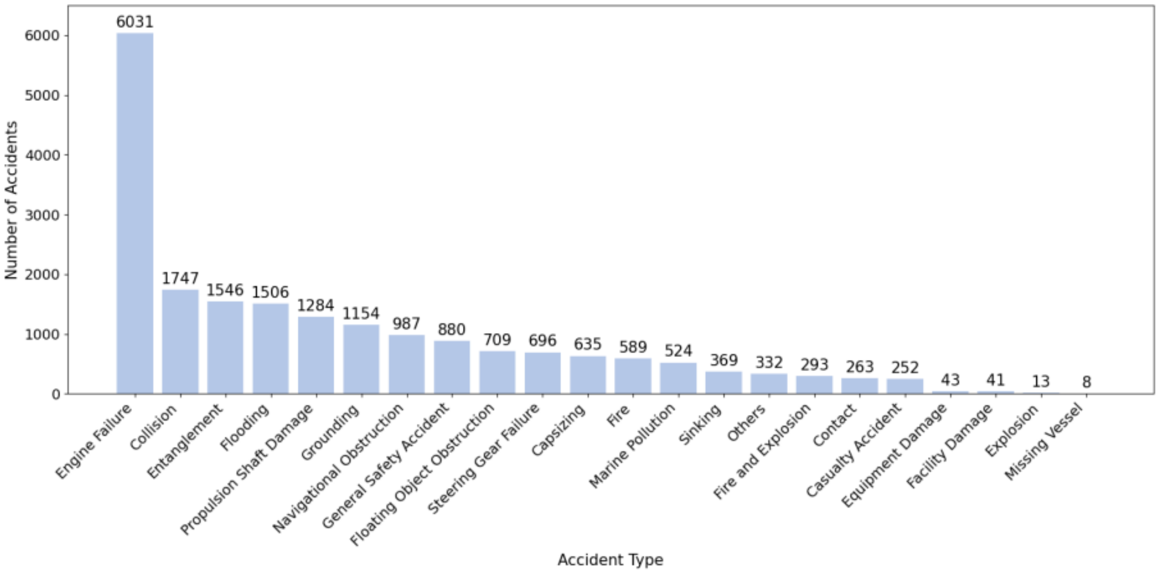


FIGURE 2. Distribution of maritime accident types

identifying the α value that best reflects accident severity based on meteorological data. A Multilayer Perceptron (MLP) model was trained using eight meteorological variables as input and the severity score as output. The α value was varied from 0.05 to 0.95 in increments of 0.05, and the value that minimized the MSE [13] was selected. This optimization aims not only to enhance predictive accuracy but also to derive a severity index that more realistically reflects the relationship between meteorological conditions and accident outcomes. In practice, maritime accident severity is used as a key indicator for prioritizing emergency response and allocating safety resources. Therefore, minimizing the prediction error based on meteorological variables helps identify the α value that best captures their causal influence on accident severity.

2.3. **Weighted KDE mapping.** KDE is a non-parametric method used to estimate the unknown density function of a random variable [9]. In this study, KDE was applied to generating a spatial risk map. The analysis domain was defined as the geographic maritime region of South Korea, spanning latitudes 33 to 39 and longitudes 124.0 to 132.0, as suggested by [13]. We divided the area into a 100 × 100 grid, following previous studies [7]. The severity scores of all accidents occurring within each grid cell were aggregated to calculate the total severity for that cell. Then, using the center point of each grid cell as the reference coordinate and the aggregated severity as the weight, a weighted KDE map was generated. The formulation for the weighted KDE is provided in Equation (2).

$$\hat{f}(x) = w_i \frac{1}{nh^d} \cdot K\left(\frac{x - x_i}{h}\right) \tag{2}$$

In this context, $\hat{f}(x)$ represents the estimated density at location x, n is the number of grid cells, h is the bandwidth, and d is the dimensionality (two in this study). w_i denotes the severity weight of the ith grid cell, x_i is the center coordinate of the ith cell, and $K(\cdot)$ is the kernel function, which is set to a Gaussian function in this study. The weighted KDE-based approach addresses the limitations of discrete grid-based visualization by smoothly connecting information across adjacent cells, thereby generating a more continuous and realistic spatial risk distribution map.

2.4. **SHAP application and analysis.** SHAP is an Explainable Artificial Intelligence (XAI) technique based on the Shapley value from game theory, which quantifies each feature's contribution to the model prediction [14]. In this study, SHAP was applied to interpreting the relationship between meteorological variables and predicted accident severity at both national and regional levels. For regional interpretation, separate MLP models were constructed for the four locations: Busan, Donghae, Mokpo, and Incheon. SHAP analysis was then applied to each model to identifying key meteorological factors influencing accident severity in each area. These maritime regions correspond to the jurisdictions of local maritime safety tribunals: Busan (Busan Metropolitan City, Ulsan Metropolitan City, Gyeongsangnam-do), Incheon (Incheon Metropolitan City, Seoul, Gyeonggi-do, Chungcheongnam-do, Chungcheongbuk-do, Jeollabuk-do), Mokpo (Jeollanam-do, Jeju Special Self-Governing Province), and Donghae (Gyeongsangbuk-do, Gangwon-do).

3. Experiments.

This section presents the experimental setup and results. The experiments are composed of the following three components:

1) Optimize the parameter α used in the calculation of accident severity scores by employing a deep learning model;
2) Construct a spatial risk map based on weighted KDE to identify high-risk areas for maritime accidents;
3) Apply SHAP to identifying key meteorological factors affecting accident severity and generate global and regional scenarios.

3.1. **Experiments setup.** The model was implemented using Python and PyTorch, and an MLP was trained for accident severity prediction. The MLP architecture consisted of two hidden layers with 64 and 32 units, respectively, each using the ReLU activation function. Training was performed for 100 epochs using the Adam optimizer with a learning rate of 1×10^{-3}. The MSE was used as the loss function. The dataset was split into 80% for training and 20% for testing to conduct the experiments.

3.2. Experiments results.

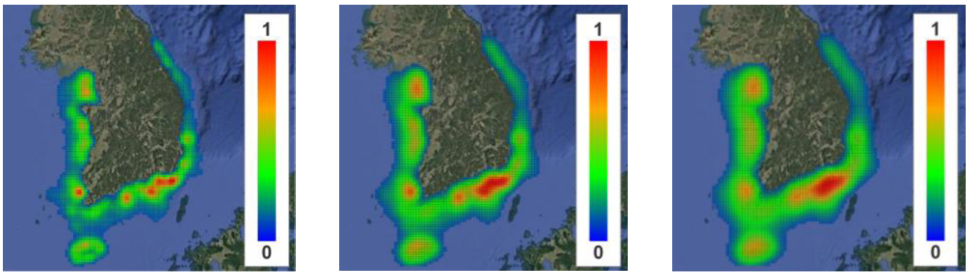
3.2.1. *Severity optimization results.* The parameter α, which controls the weighting between categorical severity and casualty information in the severity calculation, was optimized through experimentation. The model achieved the lowest MSE when $\alpha = 0.8$, as shown in Table 1. This result suggests that, compared to previous studies, optimizing the weighting of information used to determine accident severity clarifies the evaluation criteria and enables more accurate severity estimation.

TABLE 1. Optimization results for the weight parameter (α)

α	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50
MSE	0.1770	0.1302	0.1258	0.1226	0.1135	0.0929	0.0823	0.0801	0.0677	0.0678
α	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	–
MSE	0.0647	0.0574	0.0561	0.0553	0.0532	**0.0522**	0.0542	0.0527	0.0573	–

3.2.2. *Weighted KDE map.* The resulting KDE map is visualized in Figure 3.

When accident severity is derived and visualized by individual grids, areas between high-severity grids may not be recognized as risky if no accidents occurred within them. However, as shown in Figure 3, the KDE map overcomes this limitation by smoothing discrete grid boundaries, enabling more effective detection of potential high-risk zones and improving the interpretability of spatial risk distribution. Moreover, the bandwidth parameter (h) can be flexibly adjusted, allowing users to select an appropriate level of smoothing for different contexts, which makes the KDE map highly adaptable for policy design and risk management.



(a) $h = 10$ (b) $h = 15$ (c) $h = 20$

Figure 3. Kernel Density Estimation (KDE) risk maps under different bandwidth (h)

3.2.3. *SHAP analysis.* To interpret the influence of meteorological variables on accident severity prediction, SHAP dependency plots were analyzed for the eight input variables (Figure 4). The analysis revealed that the most variables exhibited similar patterns of impact. Humidity, cloud cover, temperature, visibility, and UV index all showed U-shaped relationships, indicating that accident severity increase when the values are either too low or too high reflecting the influence of extreme environmental conditions. Wind speed showed a clear increase in SHAP values, implying that strong winds have a direct effect on accident severity. Dew point was negatively associated with severity, suggesting that dryness or low humidity may indirectly increase risk. For precipitation, accident severity was higher when rainfall was low (below 10 mm), but began to rise again with increasing rainfall beyond 10 mm. This suggests that during light rain or calm conditions, reduced vigilance may increase risk, whereas heavy rainfall may compromise navigational stability due to decreased visibility, higher wave height, and rapidly changing wind direction and speed.

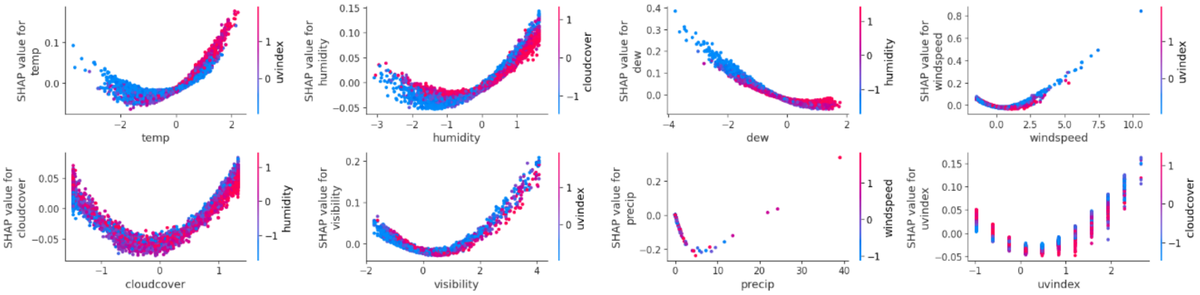


Figure 4. SHAP dependency plots for all meteorological features

Through SHAP analysis, the impact of each variable on accident severity could be quantitatively assessed. This enabled the visual identification of nonlinear effect patterns and the presence of threshold values that are difficult to capture through simple correlation analysis. These insights are expected to support the development of more effective accident prevention and response strategies, such as adjusting alert levels for specific meteorological ranges or establishing environmental thresholds to ensure navigational safety.

To reflect regional differences in meteorological conditions and accident patterns, separate MLP models were built for Busan, Donghae, Mokpo, and Incheon, followed by SHAP analyses for each region. Table 2 presents the SHAP values and feature rankings from these regional models, showing the influence of meteorological variables on accident severity. For comparison, SHAP values were normalized to sum to 100 per region.

Table 3 presents a summary of maritime accident severity across four regions, including regional impact levels, characteristic environmental features, key meteorological variables,

Table 2. SHAP values and feature rankings by maritime area

Maritime area	Rank							
	1	2	3	4	5	6	7	8
Busan	Uvindex (19.84)	Windspeed (17.14)	Temp (13.22)	Dew (12.4)	Humidity (12.37)	Visibility (12.09)	Cloudcover (10.88)	Precip (2.06)
Donghae	Temp (18.01)	Visibility (17.06)	Windspeed (15.43)	Cloudcover (13.92)	Uvindex (13.5)	Dew (10.59)	Humidity (9.52)	Precip (1.96)
Mokpo	Temp (19.83)	Cloudcover (19.06)	Visibility (14.68)	Uvindex (13.35)	Windspeed (11.64)	Dew (10.90)	Humidity (8.46)	Precip (2.08)
Incheon	Temp (16.38)	Uvindex (15.45)	Visibility (15.08)	Cloudcover (14.60)	Windspeed (13.55)	Dew (10.26)	Humidity (8.89)	Precip (5.78)

Table 3. Summary of regional maritime accident severity characteristics and key factors

Maritime region	Severity impact (%)	Key variables	Scenarios
Busan	26.2	UV index, Wind speed, Temperature	- Strong solar radiation and high temperatures may cause heat stress and reduce concentration, leading to accidents. - Strong winds and typhoons in summer may destabilize navigation and damage equipment.
Donghae	11.5	Temperature, Visibility, Wind speed, Cloud cover	- Sea-air temperature differences may cause fog and reduce visibility, leading to collisions. - Strong winter winds may reduce maneuverability and mooring stability, increasing the risk of grounding or docking accidents.
Mokpo	37.3	Temperature, Cloud cover, Visibility	- Narrow waterways and numerous islands cause frequent localized fog by hindering air circulation, reducing visibility and increasing the risk of collision or reef contact. - High cloud cover reduces visibility and raises the likelihood of judgment errors.
Incheon	25.0	Temperature, UV index, Visibility, Cloud cover	- Yellow dust and fog in spring reduce visibility, increasing accident risks. - High temperature and UV exposure may lead to heat fatigue and reduced alertness, contributing to accidents.

and accident scenarios. Each maritime region shows distinct weather patterns that influence accident severity. Busan tends to be affected by strong solar radiation and frequent typhoons, while Donghae is more vulnerable to fog and harsh winter winds. Mokpo is exposed to increased risk as its complex coastal topography disrupts air circulation and prolongs air residence time, leading to frequent localized fog and reduced visibility. Incheon experiences seasonal dust, heat, and cold waves that contribute to maritime hazards.

4. **Conclusions.** This study proposed a framework for continuous mapping of maritime accident severity and identifying key contributing factors using meteorological data and XAI techniques. The accident severity index was redefined by integrating categorical severity levels with casualty information, where the weighting parameter α was optimized through deep learning to reflect their relative importance. A weighted KDE approach was applied to visualizing spatially continuous high-risk areas, effectively addressing the

limitations of traditional grid-based and frequency-only methods. Furthermore, SHAP analysis was used to quantitatively interpret the influence of each meteorological variable on maritime accident severity at both global and regional levels. The results highlighted variables such as wind speed, temperature, and visibility exhibit strong nonlinear effects on severity. Regional analysis revealed that the key meteorological factors influencing accident severity varied by location, reflecting the spatial heterogeneity of weather conditions and local maritime environments. The proposed framework offers a practical tool for proactively identifying and monitoring high-risk zones using meteorological data. In future work, accident severity could be redefined based on pre-accident meteorological conditions, which would overcome the limitations of conventional post-incident interpretations and support the development of a predictive and proactive modeling framework. The current dataset (2018-2023) offers limited coverage of long-term climate variability, and extending the period would enhance the reliability of severity assessments under climate change. In addition, since the frequency and severity of accidents vary by type, it would be beneficial to apply differentiated severity weights accordingly. A type-sensitive weighting scheme could improve the accuracy and fairness of the risk index, while also enhancing the interpretability and practical utility of the model. Furthermore, the optimized severity index could be validated against actual economic or ecological loss data to provide external confirmation of its real-world applicability.

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