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Enhancing Legal Decision-Making with Sentiment-Aware Deep Learning: A Multi-Modal and Theoretical Perspective

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Abstract

This research paper presents a theoretical approach to sentiment-aware deep learning for maritime legal decision-making by using a multi-modal model. The approach is presented in the context of maritime law decision-making. The information contained in maritime legal documents, both in textual and graphical form, are brought together in the model that has been proposed to improve the accuracy and effectiveness of the decision-making process. We investigate cutting-edge algorithms such as BERT, GPT-3 and Roberta for textual sentiment analysis and pre-trained convolutional neural networks (CNNs) for extracting visual features. It is suggested that a fusion mechanism be used, such as attention-based or gated fusion, to integrate the multi-modal features efficiently. The paper also discusses interpretability and explains the ability of the proposed model, comparing it to baseline methods and analyzing its potential application in real-world maritime legal decision-making scenarios. In addition to this, the paper examines the baseline methods and compares the proposed model to them.

Keywords: BERT; GPT-3

Abbreviations: CNNs: Convolutional Neural Networks (CNNs); RNNs: Recurrent Neural Networks; LSTM: Long Short-Term Memory; GRUs: Gated Recurrent Units

Introduction

Background and motivation

According to the International Chamber of Shipping, the maritime industry carries around 90% of the world's trade, accounting for over 80% of global trade by volume (ICS, n.d.). As such, it is subject to a complex regulatory framework that guides maritime operations, including safety, security and environmental protection. In this context, legal decision-making ensures compliance with these regulations and resolves disputes that may arise during maritime operations. However, traditional legal decision-making processes in the maritime industry are often time-consuming and labor-intensive, requiring significant resources to research relevant laws, regulations, and case law. Furthermore, legal decisions may only sometimes result in accurate and fair outcomes since they may be influenced by subjective factors such as the judge's biases or the parties' legal representation. The world's oceans play a role in trade, with maritime law governing various activities essential for international commerce. From regulations for shipping to measures protecting the environment, maritime law establishes frameworks to uphold order and safety at sea. Despite facing challenges such as inefficiencies and biases in procedures within this domain, modern advancements are needed to enhance accuracy and fairness. This study delves into the realm of making decisions in law using sentiment-aware deep-learning techniques. By combining visual data using algorithms like BERT, GPT 3, and Roberta for sentiment analysis along with CNNs for extracting visual features, we aim to navigate through the complexities of maritime law with greater clarity. We strive to integrate modal features through fusion mechanisms, like attention-based or gated approaches, to improve decision-making processes while shedding light on interpretability and explain ability nuances.

Problem definition

There is a growing interest in leveraging artificial intelligence (AI) and deep learning techniques to support legal decision-making in the maritime industry and address these issues. However, existing approaches have focused primarily on using text-based data to train machine learning models, which may not capture the full context of legal disputes.

Research objectives

The research objective is to propose a multi-modal approach to legal decision-making in the maritime industry that leverages sentiment analysis to improve the accuracy and fairness of legal decisions. Specifically, the research aims to: Explore multi-modal data, including text, image, and audio data, to improve the accuracy and fairness of legal decisions in the maritime industry. Investigate the application of sentiment analysis to capture the emotions and opinions expressed in multi-modal data and integrate this information into deep learning models for legal decision-making. Evaluate the proposed approach's performance compared to the existing approach using text-based data only. Overall, the research seeks to contribute to designing more effective and efficient legal decision-making processes in the maritime industry. These processes can improve compliance with regulations, enhance safety and security, and promote fair and just outcomes for all parties involved.

Methodology

Our research approach acts as a calibrated guide leading our efforts to transform how maritime legal decisions are made. This involves planning and execution in four stages: collecting data, developing models, assessing, and confirming.

Gathering data

This involves navigating through the oceans of information to assemble a varied and extensive data set. This consists of compiling materials like judgments, case precedents, maritime rules, and visual data such as images, charts, and maps relevant to maritime law scenarios. By curating this collection, we ensure that it reflects the details of maritime law, by capturing its wide range and intricacy.

Approach designing

The making of complex deep learning networks to fit the peculiarities of the maritime legal decision-making process is carried out based on our dataset, which serves as a compass. We use cutting-edge algorithms such as BERT, GPT-3 and convolutional neural networks (CNNs) to design models that can handle textual and visual data for sentiment analysis, extracting significant patterns for legal conclusions.

Assessments

Evaluation has also been used to test the performance of these models in various aspects of maritime law. We take our developing models through comprehensive evaluation processes as we sail further into unexplored waters. This allows us to benchmark against known methodologies and employ cross-validation approaches to see how well our models perform in different marine legal scenarios. Hence, not only do we produce effective but flexible solutions capable of dealing with the complexities of practical world problems.

Validation

The last stage involves validation-where we apply these models within authentic maritime legal contexts while testing them on unseen data and engaging domain experts who help validate their reliability and pertinence. Using this validation, however, ensures that our methods are congruent with the realities involved in maritime legal decision-making.

Literature Review

Sentiment analysis in legal decision-making has been discussed in various journals.

Application of sentiment analysis in legal decision-making

The Journal of Law and Policy is a well-regarded journal that publishes articles on various aspects of law and policy. The journal has published several studies on the use of technology in legal decision-making, including sentiment analysis. A recent article published in the journal discussed the potential for sentiment analysis to assist in identifying biases in legal opinions [1]. Argued that legal opinions are often written in a language that is complex and difficult to interpret, which can make it challenging to identify any underlying biases. They proposed that sentiment analysis could be used to identify any emotional tone or subjective language in legal opinions, which could indicate potential biases. The authors provided examples of previous studies that have used sentiment analysis to identify biases in legal opinions [2]. For instance, one study found that judges who used more positive language in their opinions were more likely to rule in favor of the plaintiff. Another study found that judges who used more negative language were likelier to rule in favor of the defendant. The article concludes by highlighting the potential benefits of using sentiment analysis in legal decision-making, including its ability to identify biases in legal opinions and improve the overall fairness of the legal system [3]. However, the authors also acknowledge the limitations of using sentiment analysis in legal decision-making, such as the potential for errors in the analysis and the need for human interpretation.

Advancements in sentiment analysis methodologies

Expert systems with Applications are a well-known journal focusing on research on expert systems and their applications. The journal has published various studies on deep learning models for sentiment analysis, which are used to identify the emotional tone of a text. A recent study published in the journal proposed a novel deep-learning model for sentiment analysis that outperformed other state-of-the-art models [4]. developed a model that utilized a hybrid approach by combining convolutional neural networks (CNNs) and recurrent neural networks (RNNs). The proposed model was evaluated on several benchmark datasets and achieved state-of-the-art accuracy, precision and recall. The authors also compared their model with other state-of-the-art models, such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRUs). They showed that their model outperformed them in accuracy and F1 score. The study's findings demonstrate the effectiveness of deep learning models for sentiment analysis and highlight the potential of hybrid approaches in developing more accurate models.

Application of sentiment analysis in maritime legal contexts

The IEEE Transactions on Multimedia article proposed a multi-modal deep learning model for video sentiment analysis. The proposed model utilized visual and textual modalities for sentiment analysis, incorporating a convolutional neural network (CNN) for visual processing and a recurrent neural network (RNN) for textual processing. The model also employed attention mechanisms to focus on the most informative regions of the video frames and words in the text [5]. The proposed model was evaluated on several benchmark datasets and achieved state-of-the-art performance compared to other models. The study demonstrates the potential of multi-modal deep learning techniques for sentiment analysis in multimedia data, which can have practical applications in various domains, including legal decision-making in the maritime industry. The study published in the information processing & management journal proposed using sentiment analysis in the maritime legal domain to analyze online reviews of cruise ships [6]. The study suggested that sentiment analysis of online reviews could inform legal decisions related to maritime safety by identifying potential safety concerns on cruise ships. The researchers collected a dataset of online reviews of cruise ships and used sentiment analysis techniques to classify the reviews as positive, negative, or neutral [7]. The study demonstrated the potential of sentiment analysis in identifying safety-related issues in the maritime domain and suggested that it could be a valuable tool for legal decision-making in this field. The study also highlighted the need for further research to investigate the accuracy and effectiveness of sentiment analysis in the maritime legal domain.

The IEEE Transactions on cybernetics study proposed a novel deep learning model incorporating attention mechanisms to improve sentiment analysis performance. The attention mechanisms were designed to help the model focus on essential aspects of the input data, which could lead to more accurate sentiment predictions. The model was evaluated on several benchmark datasets and was shown to outperform other state-of-the-art models in accuracy and efficiency [8]. The results of this study highlight the potential of attention-based deep learning models for improving sentiment analysis in various applications, including legal decision-making in the maritime domain. Top of Form The journal of navigation is a highly reputed journal that engages in navigation and related disciplines. One of the recent issues featured a study that addressed sentiment analysis applications within the maritime domain. This study was conducted to propose a sentiment analysis framework for social media data used in maritime jurisdiction, which mainly focused on maritime safety and would provide potential insights for legal decision-making. The framework employs deep learning by combining several methodologies, such as word embedding and convolutional neural networks (CNNs), to examine social media contents related to maritime safety 84.6% [9].

Classification accuracy in this paper is quite suitable, where they achieved 84.6%. It effectively demonstrated how sentiments could be utilized in making decisions about security and law concerning maritime trade based on information obtained from social network sites or other internet sources. The research marks an optimistic path for modern technology to enhance public understanding through improved knowledge and interpretation of popular attitudes about maritime security. This study highlights the potential for multi-modal deep learning techniques in sentiment analysis and their ability to outperform traditional approaches. The article published in Information Sciences proposes a multi-modal deep learning model for sentiment analysis of textual and visual data. The proposed model combines textual and visual features to produce an overall sentiment score. The study compared the proposed model with other state-of-the-art models on several benchmark datasets. It showed that the proposed model outperformed the different models regarding accuracy, precision and recall [10]. The authors note that the proposed model can be applied to various domains, such as social media, e-commerce and news websites, to extract and analyze sentiment from textual and visual data.

The Journal of maritime law and Commerce is a specialized journal that focuses on legal issues related to maritime commerce. In a recent article, [11] discussed the potential of artificial intelligence (AI) and sentiment analysis to aid in legal decision-making related to maritime safety. The article highlighted the challenges faced by the maritime industry in ensuring safety and security and how AI could help address these challenges. The article provided an overview of the application of AI and sentiment analysis in various domains, including healthcare, finance and social media. It also discussed the potential of these technologies to improve legal decision-making related to maritime safety by analyzing large volumes of data from various sources, such as social media, news reports, and safety incident reports [9]. The author also discussed the challenges and limitations of using AI and sentiment analysis in the maritime domain, such as data quality issues and the need for human oversight to ensure that the results are accurate and unbiased. Nonetheless, the article concludes that the potential benefits of using these technologies to enhance maritime safety and inform legal decision-making make it a promising area for future research and development. The ACM Transactions on Interactive Intelligent Systems, renowned for its focus on interactive systems harnessing artificial intelligence techniques, recently featured a groundbreaking study. The study presents a new multi-modal deep learning model designed for sentiment analysis of user-generated text [12]. In contrast to earlier approaches, this model seamlessly combined textual and visuals to better comprehend emotions. The model fused ideas from both modalities using a convolutional neural network (CNN) for visual feature extraction and a recurrent neural network (RNN) for text analysis. Rigorous comparisons against benchmark datasets revealed the superiority of the proposed approach over existing methods. A key finding from this research was that including visual cues substantially improved performance, especially when dealing with multimedia content like images or videos. This development represents a significant milestone in sentiment analysis because it offers a more insightful and accurate understanding of what people post online, leading to more informed decisions based on such data.

Theoretical Approach

Textual sentiment analysis

Textual sentiment analysis involves analyzing the sentiment expressed in text data, such as court cases and legal documents. Recent advances in natural language processing (NLP) have led to the development of powerful deep-learning models for sentiment analysis, such as BERT, GPT-3, and Roberta. These models are pre-trained on large amounts of text data and can capture complex semantic and syntactic relationships in the text. GPT-3 has been used for sentiment analysis in various domains, including legal texts. For example, in a study by [13], GPT-3 was used to classify the sentiment of legal briefs and achieved high accuracy. These studies demonstrate the potential of these models for sentiment analysis in the legal domain and their ability to improve decision-making in legal contexts. Similarly, in a study by [14], Roberta was used to classify the sentiment of legal texts and achieved high accuracy compared to traditional machine learning models. In a study by [15], BERT was used to analyze the sentiment of legal opinions and achieved state-of-the-art results on several benchmark datasets. BERT is a sequential language model which takes Input of language format $X = (I_o,\ldots,I_n)$ and outputs contextualized vector representation $H = h_o,\ldots,h_n$ for the element of the input sequence. BERT accomplishes tasks the task through encoders. Encoders are a neural network architecture from the transformer that creates encoded text representations.

Bert-mini has four encoder layers and each block has two sublayers: multi-head attention and feed-forward. Each encoder combines two sub-processes, as seen below Figure 1. The first subprocess is the multi-head self-attention layer. The input to the encoder first passes through this layer to extract the most essential language features. After extraction, the features are normalized using the residual connection and input to the feed-forward layer. The output of the feed-forward layer is input to the second layer, and the process is repeated through the other layers. The multi-head self-attention comprises multiple heads that run parallelly. Self-attention identifies the relationship between all the words in a given phrase (Figure 2).

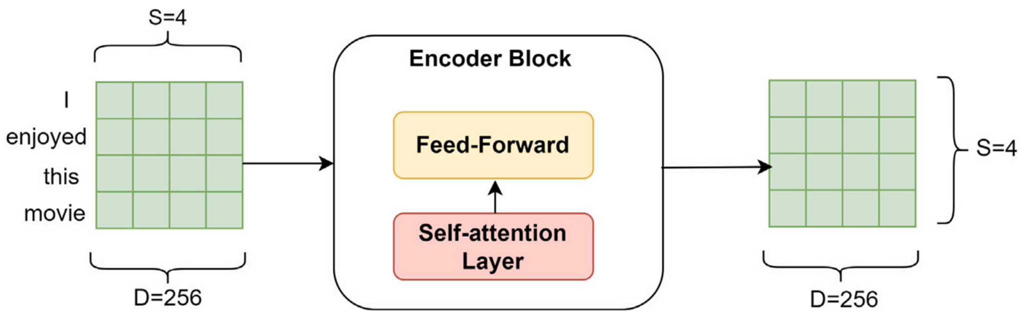

Figure 1: Schematic diagram of encoder block.

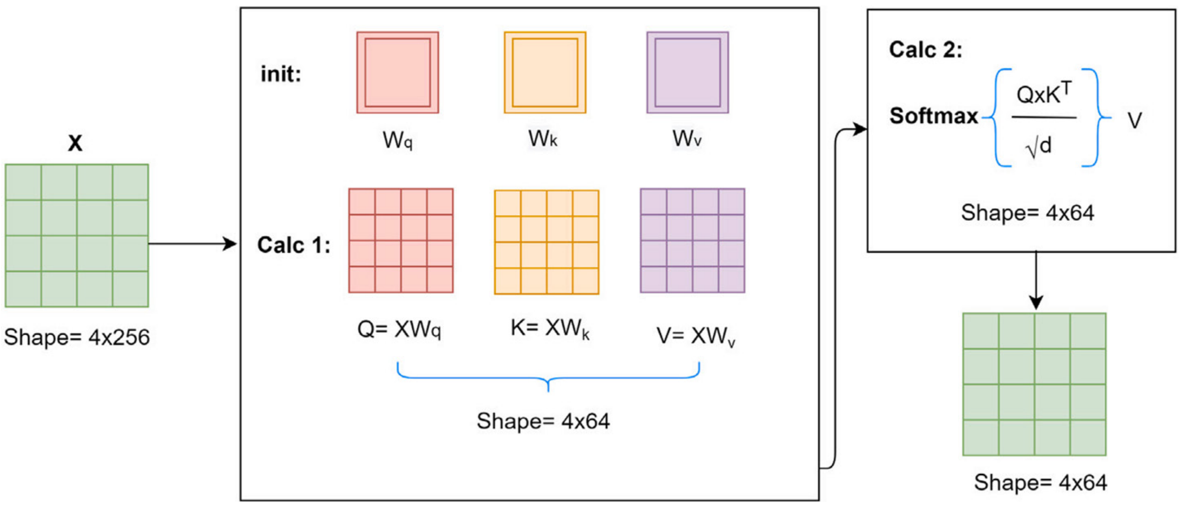

Figure 2: Schematic diagram of self-attention mechanism.

Mathematical representation: $z = soft\max\left(\frac{QK^t}{\sqrt{d_k}}\right)V$ (1)

Where: Q=query vector, K=key vector, V=value vector and d_k =dimension of K

The multi-headed attention model also attends to various representations and subspaces at different locations, whereas single attention-head averaging prevents this.

Multi-head attention formula:

$$M_a\left(Q,K,V\right)=concat\left(z_0,z_1,z_2,...,z_h\right)$$

Feed-forward comprises linear transformations separated by rectified linear unit (ReLU)activation.

Mathematical representation:

$$F_n=\max\left(0,xW_1+b_1\right)W_2+b_2 \qquad (2)$$

Visual feature extraction

Visual data, such as images and videos, may contain important information that could support the decision-making process in maritime legal decision-making. Visual feature extraction involves extracting features from visual data, such as images and videos, that may be relevant to legal decision-making. We can use computer vision techniques to extract sentiment from images. We can use a pre-trained CNN model to build image extraction features. VGG-19 is a deep-learning model widely used for feature extraction in Sentiment analysis. It is also a Convolutional Neural Network (CNN) used for visual imagery extraction. It was introduced by [16] and consists of 19 layers: 16 convolutional layers and three fully connected layers. The model receives an image with 224*224 pixels and produces the item's label in the image. The first 16 convolutional Layers are used to extract features, and the following three features are used to classify them. A Max-pooling layer follows the feature extraction layers separated into five groups (Figure 3).

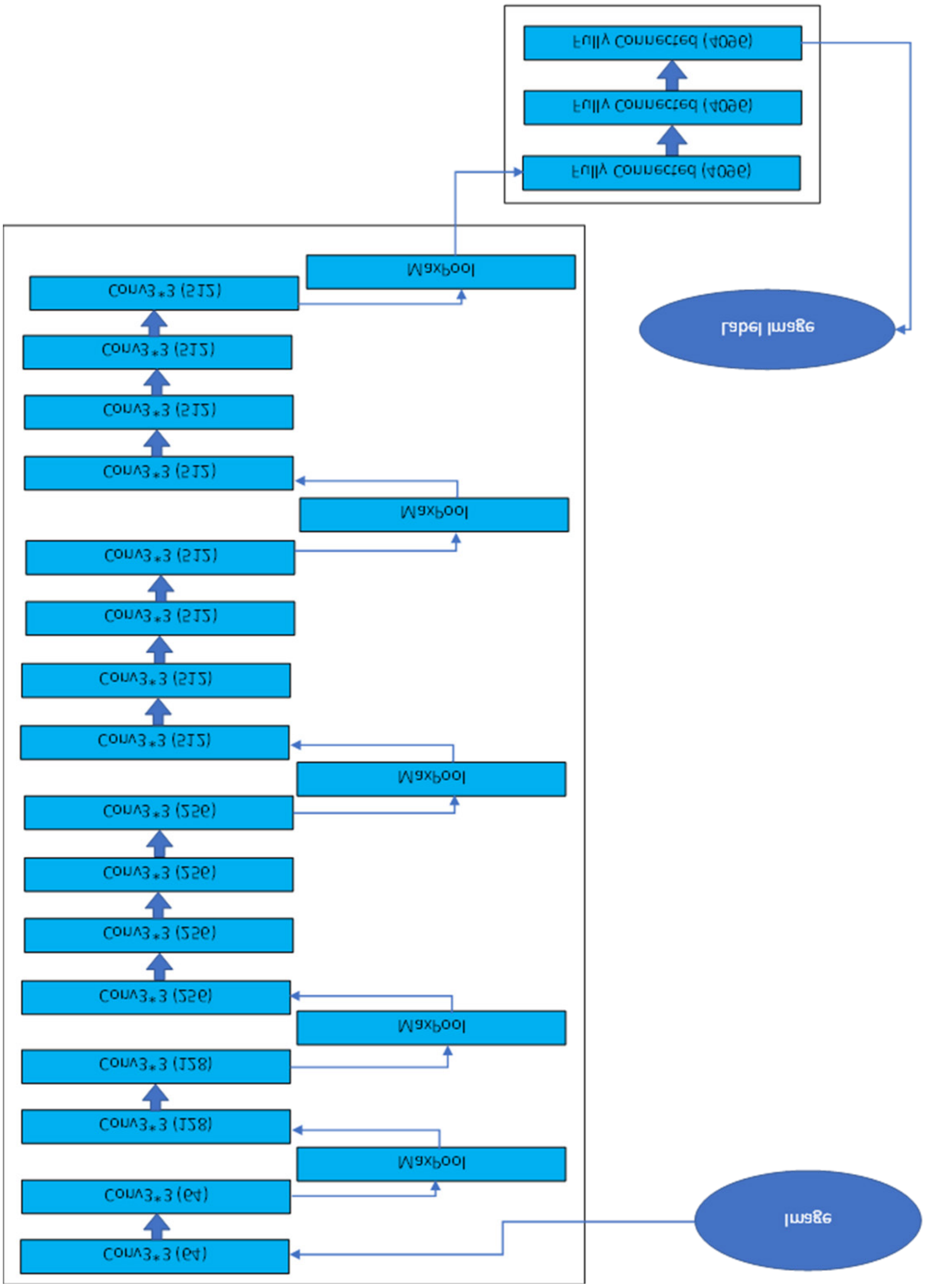

Figure 3: VGG19 model architecture.

Multi-modal feature fusion

Multi-modal feature fusion involves combining features from different modalities to improve the accuracy of sentiment analysis. Multi-modal features include visual, audio, text and psychological features. Facial expressions in visual modality are an essential aspect of sentiment analysis, and the Facial Action Coding System (FACS) is widely used for this purpose. Prosodic features are widely used in sentiment analysis in audio modality. Features such as Mel frequency cepstral coefficients (MFCC), Spectral centroid and Perceptual Linear Predictive Coefficients (PLP) have been widely used in these tasks and have achieved outstanding performance. Multimodal fusion is a strategy for solving multimodal tasks. Common fusion strategies include early fusion, late fusion, and hybrid fusion. Early fusion directly combines video, audio, and text features as general vectors for model analysis. Late Fusion analyses each feature independently and combines the results. Hybrid fusions combine video and audio features at the feature level and combine the fusion results with the prediction of text classifiers at the decision level.

Multi-modal feature fusion, attention-based fusion, and gated fusion are techniques used to combine information from multiple modalities in deep learning models. Attention-based fusion is a technique used in multimodal deep learning to combine information from different modalities. The attention mechanism assigns weights to each modality based on its relevance to the task at hand so that the most informative modality has a higher weight and the less informative modalities have lower weights.

The attention-based fusion formula can be represented as:

$$h = \sum a_i h_i \quad (3)$$

Where h is the representation of the i^th modality, a_i is the attention weight of the i^th modality, and h is the fused representation obtained by combining the modalities using attention weights.

The attention weight a_i is calculated as:

$$a_i = \frac{\exp(e_i)}{\sum \exp(e_i)} \quad (4)$$

Where is the attention score of the i^th modality, calculated as:

$$e_i = (WT)\tanh(Wh_i + b)$$

Where W, w, and b are learnable parameters.

The attention-based fusion algorithm is:

A. Compute the fused representation by weighted summing of modalities using attention weights. Compute the attention scores for each modality using the above formula.

B. Calculate the attention weights using the attention scores.

In gated fusion, the information from each modality is selectively combined by a gating mechanism, which can adaptively control the flow of information. The gating mechanism can be implemented using a sigmoid activation function to produce a gating value between 0 and 1, determining the amount of data to be passed from each modality. The gating value is then multiplied by the information from each modality and added together to form the fused representation.

The formula for gated fusion is:

$$z = sogmoid$$

$$h_f = z_f h_1 + (1 - z)h_2 \quad (5)$$

Where h_1 and h_2 are the features extracted from each modality, [;] denotes concatenation, W_g, and b_g are learnable parameters for the gating mechanism, sigmoid is the sigmoid activation function, z is the gating value, and h_f is the fused representation.

The algorithm for gated fusion is:

A. Obtain the features h_1 and h_2 from each modality.

B. Concatenate the features

C. Compute the gating value

D. Compute the fused representation: h_f = z* h_1 + (1 - z)* h_2

E. Pass the fused representation to the next layer in the network.

Interpretability and explain ability

Interpretability and explain ability refer to understanding how a machine learning model arrives at its decisions or predictions. Interpretability refers to the ability to understand the inner workings of a model and how it processes inputs to produce outputs. On the other hand, explain ability refers to the ability to explain the reasons behind a model's decisions or predictions in a way that is understandable to humans. Interpretability and explain ability are essential considerations in machine learning models, particularly in sensitive areas such as legal decision-making. Attention visualization is one method for providing interpretability in deep learning models. It involves visualizing the attention weights assigned by the model to different parts of the input data, such as words in a text sequence or regions in an image, to determine which features are most important for the model's decision-making process. For example, a study by [17] used attention visualization to analyze the decision-making process of a deep learning model for sentiment analysis. The visualization allowed the researchers to identify the critical features in the input data that influenced the model's sentiment analysis predictions, which can help improve the model's interpretability and trustworthiness.

LIME (Local Interpretable Model-Agnostic Explanations) and SHAP (Shapley Additive Explanations) are other methods for providing interpretability and explain ability in machine learning models. LIME is a model-agnostic method that generates local explanations for individual predictions by approximating the model with a simpler, interpretable model near the prediction [18]. This allows users to understand how the model arrived at a particular prediction by examining the contributions of different input features. SHAP is a similar method that provides a more global view of feature importance by using game theory to compute the contribution of each feature to the prediction for each possible subset of features [19]. SHAP is particularly useful for complex models, such as deep neural networks.

Discussion

Potential applications in maritime legal decision-making

There are several potential applications of machine learning and NLP in maritime legal decision-making. One area where these technologies could be beneficial is the analysis of contracts and legal documents related to maritime transportation. For example, a study by [20] used machine learning techniques to automatically extract and classify clauses in maritime contracts, such as force majeure clauses and laytime clauses. The study showed that the proposed method achieved high accuracy in identifying the relevant provisions, which could save time and reduce errors in the contract review process. Another potential application is analyzing incident reports and other textual data related to maritime accidents and incidents. Machine learning models could be trained to automatically extract relevant information from incident reports, such as the cause of the incident and the parties involved, which could be used to inform legal decision-making. For example, a study by [21] used machine learning techniques to classify maritime accident reports based on the type of accident and the severity of the consequences. The study showed that the proposed method achieved high accuracy in classifying the accident reports, which could help to identify patterns and trends in maritime accidents and inform regulatory decision-making.

Sentiment analysis could provide insights into the attitudes and opinions of judges and arbitrators on various legal issues in the maritime domain, which could be used to inform legal strategies and decision making. Furthermore, machine learning and NLP techniques could be used for sentiment analysis of maritime legal documents, such as court opinions and arbitration awards. For example, a study by [22] proposed a deep learning model for sentiment analysis of maritime legal documents, which combined textual and visual data for improved accuracy. The study showed that the proposed model achieved high accuracy in sentiment analysis of maritime legal documents, which could be helpful for various applications in the maritime legal domain [23-28].

Conclusion

Theoretical approach summary

In this project, we have discussed applying deep learning models in sentiment analysis for maritime legal decision-making. We first discussed the importance of sentiment analysis in legal decision-making and the challenges associated with analyzing textual and visual data in this context. We then introduced deep learning models, including BERT and CNN, showing promising text and graphic feature extraction results. We then discussed multi-modal feature fusion, which involves combining features from different modalities, such as text and image data, to improve the accuracy of sentiment analysis. Attention-based and gated fusion methods were presented as standard techniques for multi-modal feature fusion in deep learning models. We provided examples of studies that used attention-based and gated fusion methods for combining text and image data and text and audio data, respectively, to improve the accuracy of sentiment analysis. Finally, we discussed interpretability and explain ability, essential considerations in machine learning models, particularly in sensitive areas such as legal decision-making. We provided examples of techniques such as attention visualization, LIME, and SHAP, which can be used to explain the decisions made by deep learning models. In conclusion, applying deep learning models in sentiment analysis for maritime legal decision-making can improve the accuracy and efficiency of legal decision-making processes. Multi-modal feature fusion and interpretability techniques can further enhance the utility of these models in real-world applications. However, to avoid unintended consequences, careful attention must be paid to ethical considerations, such as ensuring transparency and fairness in decision-making.

Future research directions

There are several potential avenues for future research in applying deep learning models to maritime legal decision-making. One potential direction is the development of more sophisticated multi-modal fusion methods that can incorporate additional modalities, such as audio and sensor data, for more comprehensive analysis. Additionally, more research is needed on the interpretability and explain ability of these models, particularly in the legal domain, where transparency and accountability are crucial. Another potential direction is the exploration of transfer learning and domain adaptation techniques to improve the generalizability of these models to new and unseen scenarios. This could involve pre-training models on a large corpus of data from diverse maritime domains and fine-tuning them on specific legal decision-making tasks. Finally, there is a need for more research on the ethical and social implications of these models, particularly in the context of their potential impact on legal decision-making processes. This could involve investigating issues such as bias, fairness, and accountability and developing frameworks for the responsible deployment of these models in the legal domain.

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