AOMD: An Analogy-aware Approach to Offensive Meme Detection on Social Media

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Abstract

This paper focuses on an important problem of detecting offensive analogy meme on online social media where the visual content and the texts/captions of the meme together make an analogy to convey the offensive information. Existing offensive meme detection solutions often ignore the implicit relation between the visual and textual contents of the meme and are insufficient to identify the offensive analogy memes. Two important challenges exist in accurately detecting the offensive analogy memes: i) it is not trivial to capture the analogy that is often implicitly conveyed by a meme; ii) it is also challenging to effectively align the complex analogy across different data modalities in a meme. To address the above challenges, we develop a deep learning based Analogy-aware Offensive Meme Detection (AOMD) framework to learn the implicit analogy from the multi-modal contents of the meme and effectively detect offensive analogy memes. We evaluate AOMD on two real-world datasets from online social media. Evaluation results show that AOMD achieves significant performance gains compared to state-of-the-art baselines by detecting offensive analogy memes more accurately.

Keywords: Offensive Meme, Analogy-aware, Multi-modal Learning

1. Introduction

As the popularity of social networks continues to increase, social media platforms become an attractive breeding ground for amplifying offensive activities (e.g., hate speech, cyberbullying). People are increasingly exposed to online offensive content in recent years. For example, approximately 44% of Americans were subjected to online hate and harassment in 2020, and 28% of online

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social media users have experienced severe purposeful online harassment (e.g., sexual harassment, stalking, physical threats). Social media platforms and researchers have been endeavoring to combat online offensive content. Many solutions have been developed to address cyber offensive behaviors. Examples include hate speech detection, cyber racism recognition, and online harassment identification. In this paper, we study an important problem of detecting offensive analogy memes on online social media where the visual content and the text/caption of the memes together make an analogy to convey the offensive information.

Our problem is motivated by the prevalence of image-based content on online social media. Images often contain rich information and have been a key and attractive medium for people to create and share on social media. For example, an average of 95 million photos are uploaded to Instagram daily and more than 40% of tweets contain visual content. In addition, social media posts with images are more likely to attract user’s attention than those without (e.g., tweets with images can achieve 150% more retweets than the tweets without image). However, the widespread presence of images on social media also provides opportunities for the dissemination of offensive contents. In particular, sophisticated content creators increasingly favor the image as the carrier to propagate offensive information that is implicitly expressed with the accompanying text embedded in the image. Such kind of images can circumvent existing content censorship that focuses on the explicit indecent contents (e.g., sexual images, hateful vocabulary). Therefore, it is critical to effectively identify these image-driven offensive content to curb the spread of offensive information and reduce the propagation of extreme ideology on online platforms.

In this paper, we focus on an emerging phenomenon on social media where the visual content of an image together with the auxiliary text superimposed on or associated with the image jointly make an analogy to convey offensive information to the audience of the post. We refer to such kind of content as offensive analogy meme. Figure 1 shows four examples of the offensive analogy memes from online social media. Figure 1(a) used an analogy of a black pig to taunt the appearance of a Black plus-size model. Figure 1(b) delivered an implicit analogy that Jewish people are taking advantage of Black people to attack the White community. Similarly, Figure 1(c) showed a favor of White privilege using an analogy of animals, and Figure 1(d) leveraged the analogy of the quiet vs. energetic behavior on the train to reveal the hateful attitude against Black people. The goal of this paper is to automatically and accurately identify such offensive analogy memes on online social media.

Recently, several multi-modal solutions have been proposed to address the offensive meme detection problem on social media. However,
Image (a) and (b) were image-only posts. Image (c) was posted with a text description “The world is a better place because of White man.” Image (d) was posted with a text description “Civilized vs. decriminalized...Ship them all to Africa.”

Figure 1: Examples of Offensive Memes on Social Media

these solutions only focus on a direct combination of the multi-modal features from the visual content and embedded captions but ignore the implicit relation between the visual and textual contents, and the analogy they deliver together. One important observation of the above examples (Figure 1) is that these offensive analogy memes do not necessarily contain any explicit offensive or hateful content (e.g., hate speech or image) that can be leveraged to quickly detect them. Therefore, the detection of offensive analogy meme is a non-trivial problem and cannot be fully addressed by existing solutions. We elaborate the key challenges of solving this problem below.

Analogy Awareness. The first challenge of detecting offensive analogy meme lies in correctly capturing and understanding the analogy expressed by the meme. For example, the analogy between the “black bowling ball hits the white bowling pins” and the “Black people ruin the White community” in Figure 1(b) is critical to detect that offensive meme. However, the extraction of such analogy often requires a holistic analysis of the visual content, embedded caption, and user comments of the meme if available [6]. Moreover, the analogy of the offensive meme can also hide in the contextual information (e.g., the text description associated with the meme). For example, Figure 1(c) will go undetected if we ignore the analogy between the “WHITE” caption in the image and the “white man” in the text description. Such a meme can be completely
appropriate when it appears in the wildlife protection forum. The existing solutions that focus on the image or text content itself are often insufficient to capture the analogy in such offensive memes [6]. Therefore, such analogy has to be carefully captured and considered in the process of offensive meme detection on social media.

Complex Multi-modal Analogy Alignment. The second challenge of detecting offensive analogy meme lies in the accurate alignment of the complex analogy across different data modalities in a meme post. For example, existing solutions for embedded caption extraction highly rely on the optical character recognition (OCR) technique [9]. However, the OCR technique only focuses on recognizing all the characters in an image and can often recognize irrelevant content (e.g., “CALVIN KLEIN” in Figure 1(a)). Such irrelevant OCR texts may lead to the identification of incorrect analogy in the meme. Moreover, it is also important to accurately capture the analogical relation between the visual and textual content in the meme. For example, as the image shown in Figure 1(b), the implicit offensive content against Jewish people and Black people cannot be captured if the visual content and textual captions are incorrectly matched. The positions of the visual content and embedded captions have to be carefully considered to capture the analogy (i.e., bowler - “Jews”, black bowling ball - “Black people”, white bowling pins - “A quiet, peaceful, functioning society” in the above example). However, current multi-modal meme solutions that simply integrate visual and textual features of a meme are insufficient to capture the analogy embedded across different data modalities in the meme [10].

To address the above challenges, we develop a deep learning based Analogy-aware Offensive Meme Detection (AOMD) framework that can effectively identify offensive analogy memes on online social media. In particular, to address the analogy awareness challenge, we develop an analogy-aware multi-modal representation learning module to incorporate the content (i.e., image, embedded caption) and contextual information (i.e., text description, user comments) to identify the analogy expressed in the meme. To address the complex multi-modal analogy alignment challenge, we develop an attentive multi-modal analogy alignment module to explicitly model the relation between the visual content and textual caption in the memes. To the best of our knowledge, AOMD is the first analogy-aware deep learning based solution to detect offensive analogy memes on social media. We evaluate the AOMD framework on two real-world datasets collected from Gab and Reddit. Evaluation results show that AOMD achieves significant performance gains compared to state-of-the-art baseline methods by detecting offensive analogy memes more accurately.

2. Related Work

2.1. Social Media Misbehavior

Misbehavior has become a severe issue on social media platforms. Examples of social media misbehavior include cyberbullying [11, 12], trolling [12], hateful content [13, 14], rumors [15], and fake news [16, 17]. For example, Yao et al.
proposed an online approach with sequential hypothesis testing to detect cyberbullying events in a timely manner [18]. Cheng et al. developed a machine learning based scheme to detect troll posts by exploring users’ mood and context information on online news discussion communities [19]. Relia et al. developed a multi-level classifier to automatically identify targeted and self-narration of discrimination on social media [20]. Kumar et al. designed a multi-task learning scheme that exploits the reply stance of social media posts to identify rumors [21]. Wu et al. developed a deep learning based framework to detect fake news by tracing the propagation pattern of posts on social media [22]. However, these solutions are insufficient to detect the offensive analogy memes on social media where the offensive content are embedded in the analogy across the visual and textual content of the meme.

2.2. Hate Speech Detection

The spread of hate speech has gained much attention on online social media in recent years [23, 24]. A number of solutions have been proposed to mitigate the problem. For example, Waseem et al. proposed a critical racial theory based hate speech detection framework using n-grams and demographic information to identify racist and sexist slurs on Twitter [25]. More recently, the phenomenon of utilizing memes (i.e., a form of multi-modal media that expresses an idea or emotion) to spread offensive content has been observed in the 2016 U.S. presidential election [5]. Sabat et al. developed a deep learning framework to automatically detect the hate speech in memes by fusing the visual and linguistic contents of the memes [4]. Chauhan et al. proposed a multi-task learning framework to simultaneously classify memes on five different tasks (e.g., offensiveness, sentiment, sarcasm) [7]. Velioglu et al. developed an ensemble learning approach to boost the performance of identifying hateful memes by incorporating classification results from multiple classifiers [8]. However, none of the existing solutions is dedicated to study the analogy in memes, which contains critical information in identifying the offensive content. In this paper, we explicitly model the analogical relation between the visual content and embedded captions to detect offensive analogy memes on social media.

2.3. Multi-modal Learning

Recently, multi-modal learning has attracted much attention in learning informative features from various types of data [26]. Applications of multi-modal learning includes multi-modal machine translation [27], visual question answering [28], image-text matching [29], and video description generation [30]. For example, Zhou et al. developed a multi-modal machine translation model that leverages visual information to assist machine translation task in distinguishing ambiguous words [31]. Yi et al. proposed a deep representation learning framework to infer answers to questions of visual content [32]. Li et al. designed a semantic reasoning network to learn the visual representation of images and align them with text captions [33]. Hori et al. proposed an attention-based multi-modal fusion framework to fuse image, audio, and motion features
to generate video descriptions [34]. However, none of these multi-modal learning solutions is dedicated to identifying and aligning the analogy across different data modalities. In this work, we propose an co-attentive multi-modal analogy alignment scheme to extract and align the analogical features from the multi-modal memes to identify offensive analogy memes.

3. Problem Definition

In this section, we formally present the offensive analogy meme detection problem on social media. We first define a few key terms that will be used in the problem definition.

Definition 1. Meme Post ($P_i$): a meme post ($P_i$) on social media contains three major components: i) meme ($M_i$), ii) text description ($D_i$), and iii) user comments ($U_i$). An example of the meme post on social media is shown in Figure 2.

![Figure 2: Example of a Meme Post on Social Media](image)

Definition 2. Meme ($M_i$): the image attachment of a meme post. The meme attachment contains two parts: the visual content ($M_{iV}$) and embedded caption ($M_{iC}$).

Definition 3. Visual Content ($M_{iV}$): the imagery content in the meme that depicts visual perceptions (e.g., the view of cities in Figure 2).

Definition 4. Embedded Caption ($M_{iC}$): the text superimposed to or naturally contained in the meme (e.g., “NIGGERS: WORSE THAN NUKES” in Figure 2).

Definition 5. Text Description ($D_i$): the optional text description of the meme post (e.g., “Hiroshima vs. Detroit” in Figure 2). The text description will be marked as an empty string for any meme post does not contain any text description.
**Definition 6. User Comments** \((U_i)\): a set of user comments associated with the post.

**Definition 7. Offensiveness**: the meme post is considered offensive (denoted as \(y_i = 1\)) if the visual content and/or the embedded caption of the meme together with its text description (if available) conveys offensive or prejudicial information against individuals or groups of people (e.g., race, gender, religion). Otherwise, it is considered non-offensive (denoted as \(y_i = 0\)).

The goal of our offensive analogy meme detection is to investigate the analogy embedded in the meme and identify its offensiveness given the meme content \((M_i)\), text description \((D_i)\), and user comments \((U_i)\). In particular, we assume \(\mathcal{P} = \{P_1, P_2, \cdots, P_N\}\) is a set of \(N\) meme posts on social media, where each meme post \(P_i\) for \(1 \leq i \leq N\) is defined as \(P_i = (M_i, D_i, U_i, y_i)\). Formally, for each \(P_i \in \mathcal{P}\), our goal is to find:

\[
\arg \max_{\hat{y}_i} Pr(\hat{y}_i = y_i | P_i), \quad \forall 1 \leq i \leq N
\]  

(1)

where \(y_i\) and \(\hat{y}_i\) are the ground truth and estimated label of the meme offensiveness, respectively.

4. Solution

![Figure 3: An Overview of the AOMD Framework](image)

In this section, we present the Analogy-aware Offensive Meme Detection (AOMD) framework to address the offensive analogy meme detection problem defined in the previous section. An overview of the AOMD framework is shown in Figure 3. The AOMD framework contains three components. First, the analogy-aware multi-modal representation learning module is designed to extract the visual, textual, and contextual features from the multi-modal contents of meme posts. Second, the attentive multi-modal analogy alignment module aims to capture the analogical relation from the multi-modal content in the meme.
Third, the supervised learning module is developed to effectively identify the offensive analogy meme in a supervised manner. We elaborate the details of each component below.

4.1. Analogy-aware Multi-modal Representation Learning Module

The multi-modal representation learning module is designed to extract key features from each element of the meme post, and learn the representation of each element across different data modalities. In particular, we focus on the visual content, embedded caption, and contextual information (i.e., text description and user comments) to capture the offensive analogy conveyed in the meme posts.

4.1.1. Visual Content Extraction

The visual content in a meme image often carries essential information to identify the offensive analogy in the meme. Current solutions on offensive meme detection often focus on the image-level visual features extracted from the entire image of the meme [35]. However, such kind of image-level features is often insufficient to capture the fine-grained visual features of the objects in the image that connect to the offensive analogy in the meme. For example, the image-level feature can capture the concept of “person and animal” in Figure 1(a). In contrast, the object-level feature can better characterize the detailed visual feature of the “black pig” and “Black model” objects, which are the essential cues to identify the offensive analogy in that meme. In order to capture such kind of analogy embedded in the visual content, we leverage both the local object-level and global image-level information to identify offensive analogy memes.

First, we extract the local visual objects and their possible positions (i.e., the bounding box of the object) in the meme. We observe that the visual features of objects in a meme are often relevant to the characteristics of the analog in the offensive analogy. For example, as shown in Figure 1(b), the visual object “black bowling ball” shares the color with the embedded caption “Black people” and the appearance of the “player” (i.e., white shirt and black pants) matches the dressing style of Jewish people (i.e., the embedded caption “Jews” in the meme). Such visual characteristics of the local visual objects in the meme are critical to understand the offensive analogy conveyed by the meme. In particular, the local visual objects and their positions are extracted using the advanced Faster R-CNN model [36] pre-trained on the MSCOCO dataset [37]. Formally, for each meme image, we define the set of extracted visual objects $V$ in meme $M_i$ as:

$$V = \{V_1, V_2, \cdots, V_{K_i}\}$$  \hspace{1cm} (2)

where $V_k = (v_k, p_k)$ represents the $k^{th}$ visual object, $v_k \in \mathbb{R}^{d \times 1}$ denotes the latent feature vector of the visual object, and $p_k \in \mathbb{R}^{8 \times 1}$ denotes the vertex coordinates of the visual object’s bounding box. $K_i$ is the number of identified visual objects in the meme $M_i$.

In addition, we also extract the global image-level visual feature by encoding the image of the meme to the latent feature space with a pre-trained convolutional visual feature extractor. We observe that the visual information of the
entire image in the meme often contain valuable clues to identify the offensive analogy. For example, the scene of “a man bowls a ball” in Figure 1(b) provides useful hints to capture the offensive analogy of “Jewish people leverage Black people to hit the White community”. In particular, the global visual feature is extracted from a commonly adopted deep convolutional neural network for visual recognition (i.e., ResNet50 [38] pre-trained on MSCOCO). We denote the global visual feature as $F^g$.

4.1.2. Embedded Caption Extraction

In addition to the visual features, we also extract the embedded captions from the meme image. In particular, the embedded caption is often superimposed over the image. Different from the implicit offensive information in the visual content, captions embedded in the meme often provide explicit and indispensable information in identifying the offensive analogy. However, it is not a trivial task to identify the exact caption that contributes to an offensive analogy in a meme. For example, the embedded captions “Gorilla” and “Africans” in Figure 4(a) makes an analogy to deliver the racism from the meme while the embedded caption “Gorilla” and “Child” in Figure 4(b) only make the meme funny.

![Figure 4: Example of Offensive and Non-offensive Memes](a) Offensive Meme (b) Non-offensive Meme

To accurately capture the embedded caption from the meme, we first use the state-of-the-art optical character recognition (OCR) tool from Google Vision API to extract the word tokens from the meme. We also record the position of the bounding box for each word token to preserve the spatial feature of the embedded captions. Formally, we denote the set of extracted word tokens $T^w$ as:

$$T^w = \{T^w_1, T^w_2, \ldots \}$$

where $T^w_j = (w_j, p_j)$ represents the $j^{th}$ word token, and $w_j \in \mathbb{R}^{8 \times 1}$ denote the recognized word and its bounding box coordinates, respectively.

A limitation of existing image OCR tools is that they primarily focus on the recognition of individual words in the image and are insufficient to capture the word-to-phrase association. For example, the embedded captions in Figure 1(b) are recognized by the OCR tool as “A quiet, peaceful, Jews functioning society

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5https://cloud.google.com/vision
Black people” which messes up the correct word-to-phrase association as “Jew”, “A quiet, peaceful, functioning society”, “Black people”. To overcome such a limitation, we design a cluster-based OCR to effectively extract the phrases (i.e., token cluster) from the meme. The word tokens are clustered based on the spatial position of the bounding boxes. In particular, word tokens belong to the same token cluster if their bounding boxes are overlapped or close to each other. We denote the set of extracted word token clusters $T^c$ as:

$$T^c = \{T^c_1, T^c_2, \ldots, T^c_S\}$$

where $T^c_s = (c_s, p_s)$ represents the $s^{th}$ word token cluster, and $c_s$ and $p_s \in \mathbb{R}^{8 \times 1}$ denote the word sequence (i.e., phrase) in the word token cluster and the word token cluster’s bounding box coordinates, respectively. $S_i$ is the number of word token clusters in the meme $M_i$.

Since each cluster contains word tokens of various lengths, we further learn the fixed-length vector representation of each cluster using a recurrent neural network (RNN) based long short term memory (LSTM) word sequence encoder [39] with pre-trained GloVe embeddings [40]. We use the LSTM encoder because it can learn the semantic meaning of word sequences by capturing the long-term word dependency in the sequence. Formally, for each word token cluster $T^c_s = (c_s, p_s)$ in $T^c$, the encoded vector representation of the word sequence is:

$$c_s = \text{LSTM}(c_s)$$

The set of vector representation of word token clusters of meme $M_i$ is denoted as:

$$C = \{C_1, C_2, \ldots, C_{S_i}\}$$

where $C_s = (c_s, p_s)$ represents the $s^{th}$ word token cluster, and $c_s \in \mathbb{R}^{d \times 1}$ and $p_s \in \mathbb{R}^{8 \times 1}$ denote the vector representation and bounding box coordinates of the word token cluster, respectively.

4.1.3. Contextual Information Extraction

In addition to the visual content and embedded captions, the offensiveness of an analogy meme on social media also depends on the context of the meme post. In particular, we focus on two types of contextual information of a meme post: the text description and user comments. We observe that both the text description from the content creators and the user comments from the viewers often contain helpful information in identifying the offensive analogy. For example, the text description of the meme in Figure 1(c) contains important information that can help capture the analogy between the “white wolf” and “white men”. In addition, the user comments in Figure 2 also provides valuable clues in assessing the offensiveness of the analogy meme (e.g., “STOP THE RACIST SH*T”). We adopt the same LSTM encoder as in caption extraction to extract the linguistic features from the text description and user comments. In particular, let $d$ and $u$ be the word sequences of the text description and
user comments, respectively. The encoded vector representations for the text description and user comments are denoted as:

\[ F^d = \text{LSTM}(d); \quad F^u = \text{LSTM}(u) \]  

4.2. Attentive Multi-modal Analogy Alignment Module

With the multi-modal features extracted from the visual content, embedded captions, and contextual information, we now present the attentive multi-modal analogy alignment module to extract the analogical feature from the multi-modal content of the memes. Existing multi-modal learning solutions primarily rely on the pre-training of features on uni-modal data (e.g., object detection on image data [38], BERT on text data [41]) to integrate cross-modal information. However, such methods often ignore the analogical relation between the visual and textual contents in meme posts and are suboptimal in detecting offensive analogy memes. For example, it will significantly reduce the possibility of catching the offensive analogy memes if we simply concatenate the visual feature of the image (e.g., “person, bowling ball, bowling pins” in Figure 1(b)) and the linguistic feature of embedded captions (e.g., “Jews a quiet, peaceful, functioning society Black people”) but ignore the analogical relation between them (e.g., “bowling ball” and “Black people”).

To address the above problem, we develop an analogy-aware attention mechanism to effectively integrate the information from different components in the meme posts. The goal of the analogy-aware attention mechanism is to learn useful features from the representation of visual objects and word token clusters that are effective in identifying the analogy of offensive memes. In particular, we observe that the visual object and word token cluster that are analogically related often appear to be in close proximity in the meme. For example, the visual object “black gorilla” is close to the word token cluster “Koko the Gorilla” in Figure 4(a) to create the analogy in that meme. To capture and preserve such a spatial proximity, we first concatenate the vector representations of the visual objects and word token clusters with their normalized bounding box positions. Specifically, let \( V = \{ \tilde{v}_1, \tilde{v}_2, \cdots, \tilde{v}_K \} \in \mathbb{R}^{d \times K} \) and \( C = \{ \tilde{c}_1, \tilde{c}_2, \cdots, \tilde{c}_S \} \in \mathbb{R}^{d \times S} \) be the feature matrices for visual object and word token cluster representations, respectively. Then the concatenated feature vectors for each \( V_k \in V \) and \( C_s \in C \) are defined as:

\[ \tilde{v}_k = [v_k, p_k] \in \mathbb{R}^{d \times 1} \text{ and } \tilde{c}_s = [c_s, p_s] \in \mathbb{R}^{d \times 1} \]  

Next, we introduce the affinity matrix in learning the attention weights in the AOMD framework. The goal of computing the pairwise affinity is to effectively capture the pairwise analogical relation between the visual objects and word token clusters in a meme. In particular, let \( V = [\tilde{v}_1, \tilde{v}_2, \cdots, \tilde{v}_K] \in \mathbb{R}^{d \times K} \) and \( C = [\tilde{c}_1, \tilde{c}_2, \cdots, \tilde{c}_S] \in \mathbb{R}^{d \times S} \) be the feature matrices for visual object and word token cluster representations, respectively. We define the pairwise affinity matrix \( E \in \mathbb{R}^{S \times K} \) as:

\[ E = \text{tanh}(C^T W V) \]
where $W \in \mathbb{R}^{d \times d}$ represents the weight parameters to be learned in the neural networks.

In addition, to effectively extract the attended features, we adopt a common co-attention strategy [42] to compute the attention map and attention weights for visual objects and word token clusters simultaneously. Intuitively, the visual object and word token cluster features that are more relevant to the offensive analogy in the meme will be given higher attention weights. Formally, the attention map for visual objects ($M_v \in \mathbb{R}^{d \times K}$) and word token clusters ($M_c \in \mathbb{R}^{d \times S}$) are defined as:

$$M_v = \tanh(W_v V + (W_c C) E)$$
$$M_c = \tanh(W_c C + (W_v V)^T)$$

(10)

where $W_v$ and $W_c$ are the weight parameters of the attention layer. The attention weights for visual objects ($\alpha_v \in \mathbb{R}^K$) and word token clusters ($\alpha_c \in \mathbb{R}^S$) are defined as:

$$\alpha_v = \text{softmax}(w_v^T M_v); \quad \alpha_c = \text{softmax}(w_c^T M_c)$$

(11)

where $w_v$ and $w_c$ are the weight parameters of the attention layer.

Using the attention weights defined above, we compute the analogically attended feature representation for the extracted visual objects and word token clusters. Formally, the attended feature vector for the visual objects ($F^v$) and word token clusters ($F^c$) are represented as follows:

$$F^v = \sum_{k=1}^K [\alpha_v]_k v_k; \quad F^c = \sum_{s=1}^S [\alpha_v]_s c_s$$

(12)

Finally, we integrate the attended feature vectors for the visual objects ($F^v$) and word token clusters ($F^c$) with the set of feature representations of the visual content ($F^g$), contextual information ($F^d$ and $F^u$) that learned from Section 4.1. In particular, these feature vectors are concatenated and input to the supervised learning module discussed in the next section to detect the offensive analogy memes.

### 4.3. Supervised Learning Module

With latent features fused from the visual content, embedded captions, and contextual information as discussed in the previous sections, we now perform the binary classification to identify offensive analogy memes. In particular, we input the learned features into a two-layer feed-forward neural network (i.e., multilayer perceptron) and a Softmax output layer that predicts the probability of a meme post $P_i$ being offensive. Formally, the output of the AOMD framework is defined as:

$$\hat{y} = \text{softmax}(\text{MLP}([F^v_i, F^c_i, F^g_i, F^d_i, F^u_i]))$$

(13)

where $\hat{y}_i$ is the estimated probability of label being 1 (i.e., offensive).
In particular, let \( y_i \) be the ground truth label (i.e., \( y_i \in \{0, 1\} \) where 0 indicates non-offensive, and 1 indicates offensive), our learning goal is to minimize the cross-entropy loss defined as:

\[
L(\theta) = \frac{1}{N} \sum_{i=1}^{N} (y_i \log \hat{y}_i + (1 - y_i) \log(1 - \hat{y}_i))
\]  

where \( \theta \) represents the parameters of the proposed neural network as shown in Equation 13. We adopt the Adaptive Moment Estimation with decoupled weight decay (AdamW) optimizer to solve our optimization problem in Equation 14. We summarize the AOMD in Algorithm 1.

**Algorithm 1** Summary of the AOMD Framework

1: **input:** meme post set \( P \)
2: **output:** \( \hat{y} \)
3: \( \triangleright \) training phase
4: **initialize:** \( F \)
5: for each \( P_i \) in \( P \) do
6: **initialize:** \( T_{c}^{i}, F_{v}^{i}, F_{c}^{i} \)
7: extract \( F_{g}, V_{i}, T_{w}^{i}, F_{d}^{i}, F_{u}^{i} \)
8: for each \( T_{c, j}^{i} \) in \( T_{c}^{i} \) do
9: assign to \( T_{c, s}^{i} \in T_{c}^{i} \)
10: end for
11: extract \( C_{i} \) from \( T_{c}^{i} \)
12: \( F \leftarrow [F_{v}^{i}, F_{c}^{i}, F_{g}, F_{d}^{i}, F_{u}^{i}] \)
13: end for
14: learn \( \theta \) by optimizing \( L(\theta) \) (Eq. 14)
15: \( \triangleright \) classification phase
16: **initialize:** \( \hat{y} = [\] \)
17: for each \( P_i \in P \) do
18: apply neural network model (Eq. 13) to predict \( \hat{y}_i \)
19: \( \hat{y} \leftarrow \hat{y}_i \)
20: end for
21: output \( \hat{y} \)

5. Data

In this section, we present the real-world datasets and labels we collected for evaluation. We observe that mainstream social media platforms (e.g., Twitter) contain a massive amount of memes. However, the collection of offensive memes on those platforms has experienced a long tail issue (i.e., only a small portion of the collected memes are actually offensive) [44]. In addition, we observe that existing datasets for offensive memes (e.g., MultiOFF [5], SemEval-2020 [6])

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1. In particular, let \( y_i \) be the ground truth label (i.e., \( y_i \in \{0, 1\} \) where 0 indicates non-offensive, and 1 indicates offensive), our learning goal is to minimize the cross-entropy loss defined as:

\[
L(\theta) = \frac{1}{N} \sum_{i=1}^{N} (y_i \log \hat{y}_i + (1 - y_i) \log(1 - \hat{y}_i))
\]  

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**Algorithm 1** Summary of the AOMD Framework

1: **input:** meme post set \( P \)
2: **output:** \( \hat{y} \)
3: \( \triangleright \) training phase
4: **initialize:** \( F \)
5: for each \( P_i \) in \( P \) do
6: **initialize:** \( T_{c}^{i}, F_{v}^{i}, F_{c}^{i} \)
7: extract \( F_{g}, V_{i}, T_{w}^{i}, F_{d}^{i}, F_{u}^{i} \)
8: for each \( T_{c, j}^{i} \) in \( T_{c}^{i} \) do
9: assign to \( T_{c, s}^{i} \in T_{c}^{i} \)
10: end for
11: extract \( C_{i} \) from \( T_{c}^{i} \)
12: \( F \leftarrow [F_{v}^{i}, F_{c}^{i}, F_{g}, F_{d}^{i}, F_{u}^{i}] \)
13: end for
14: learn \( \theta \) by optimizing \( L(\theta) \) (Eq. 14)
15: \( \triangleright \) classification phase
16: **initialize:** \( \hat{y} = [\] \)
17: for each \( P_i \in P \) do
18: apply neural network model (Eq. 13) to predict \( \hat{y}_i \)
19: \( \hat{y} \leftarrow \hat{y}_i \)
20: end for
21: output \( \hat{y} \)

5. Data

In this section, we present the real-world datasets and labels we collected for evaluation. We observe that mainstream social media platforms (e.g., Twitter) contain a massive amount of memes. However, the collection of offensive memes on those platforms has experienced a long tail issue (i.e., only a small portion of the collected memes are actually offensive) [44]. In addition, we observe that existing datasets for offensive memes (e.g., MultiOFF [5], SemEval-2020 [6])
only contain the meme images but lack of the text description and user comments which are essential for the detection of offensive memes. Therefore, we collected our own datasets for the comprehensive evaluation of the proposed AOMD scheme.

We choose two offensive meme appealing social media forums, the “Memes, memes, and more Memes” group on Gab\(^6\) and the \(r/NewOffensiveMemes\) sub-forum on Reddit\(^7\) as our data sources to collect the offensive analogy memes for our study. For each meme post, we collect the meme content, text description, and user comments. We note that meme images are diversified and rarely duplicated on these two forum-driven platforms where users often prefer posting “new” content to re-posting. Next, we invite three independent annotators to annotate the label of each meme (i.e., the offensiveness of the meme) by carefully assessing the analogy embedded in the meme content. The ground-truth labels are decided based on the majority of the three annotators. The inter-annotator agreement (i.e., Fleiss Kappa score \(^{45}\)) of the Gab and Reddit datasets are 0.47 and 0.51, respectively. A summary of the collected datasets is presented in Table 1. While our datasets are collected from offensive meme appealing forums, we observe that our datasets are not balanced (i.e., non-offensive memes are more than offensive ones), which is consistent with the observation on mainstream social media platforms. We also observe that 63.2% and 99.5% of the meme posts in the Gab and Reddit datasets contain contextual information (i.e., text description, user comments), respectively.

Table 1: Dataset Statistics

| Data Trace | Gab | Reddit |
|------------|-----|--------|
| Total Number of Collected Meme Posts | 1,965 | 1,094 |
| Number of Offensive Meme Posts | 672 (34.2%) | 380 (34.7%) |
| Number of Meme Posts Containing Analogy | 891 (45.3%) | 522 (47.7%) |
| Number of Meme Posts Containing Contextual Information | 1,242 (63.2%) | 1,089 (99.5%) |

6. Evaluation

In this section, we evaluate the performance of the AOMD framework on the real-world datasets described in Section 5. In particular, we compare the performance of AOMD with the state-of-the-art baselines from the literature. The results show that the AOMD framework achieves significant performance gains in terms of the offensive analogy meme detection accuracy compared to all baselines.

6.1. Baselines and Experiment Setting

We compare AOMD with several state-of-the-art baselines in detecting offensive analogy memes on social media.

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\(^6\)https://gab.com/
\(^7\)https://reddit.com/
• **WSCNet** [46]: a convolutional neural network based scheme that learns the sentiment representation of visual content and classifies the sentiment of an image. We use the meme image as input and train the WSCNet scheme to detect offensive analogy meme.

• **HateSpeech** [47]: a lexicon-based approach that automatically detects hate speech on social media with a set of linguistic and sentiment features. We take the embedded caption of each meme post as the input to the HateSpeech framework.

• **MultiOFF** [5]: a recent transfer learning based approach that detects offensive analogy memes by fusing pre-trained visual and linguistic features into a dense neural network (i.e., MLP).

• **HatePixel** [4]: a multi-layer perceptron classification approach that detects hate speech in images by encoding visual and textual contents into latent vectors with pre-trained models (i.e., VGG-16 for visual representations and BERT for text embeddings).

• **HatefulMeme** [10]: a recent multi-modal hateful meme detection framework that performs the detection task by leveraging the pre-trained feature from Visual BERT [48] with a MLP classifier.

We use the meme images and OCR word tokens as the inputs to the WSCNet and HateSpeech baseline, respectively. The inputs to the multi-modal baselines (i.e., MultiOFF, HatePixel, and HatefulMeme) are the same as AOMD but exclude the contextual information since none of these baselines explicitly model the contextual information. Therefore, we present the performance of three ablations of the AOMD framework for the fair comparison with baseline methods taking less input than AOMD. In the meantime, we also evaluate the contribution of the attentive multi-modal analogy alignment component in the ablation study. In particular, we consider the following ablations of the AOMD framework.

• **AOMD w/o Visual**: the AOMD framework excludes the global visual feature extracted from the visual content of each meme.

• **AOMD w/o OCR**: the AOMD framework excludes the OCR extraction of embedded captions from each meme.

• **AOMD w/o Context**: the AOMD framework excludes the contextual information (i.e., text description and user comments of each meme post).

• **AOMD w/o Attention**: the AOMD framework removes the attention layer and combines the the average visual object feature and word token cluster features by concatenation.

For all compared baselines, we use 70%, 10%, and 20% of the dataset as the training, validation, and testing set, respectively. The vector lengths of the
visual features, encoded embedded caption, text description and user comments are set to 100. We use AdamW as the optimizer and set learning rate = 0.001, $\epsilon=1e-8$, and the batch size to 32. For all other baselines, we follow the network architectures presented in the paper and carefully tune the hyperparameters to achieve the best performance of each baseline.

6.2. Detection Effectiveness

In the first set of experiments, we evaluate the detection accuracy of the AOMD framework and all compared baselines. In particular, we use a set of common metrics for binary classification to evaluate the detection performance: **Accuracy**, **F1 Score**, and **Cohan’s Kappa Coefficient (Kappa)**. The results are shown in Table 2 and Table 3.

We observe that the AOMD scheme consistently outperforms all baseline methods on all evaluation metrics on both the Gab and Reddit datasets. For example, AOMD outperforms the best performing baselines on the Gab dataset (i.e., MultiOFF) and Reddit dataset (i.e., HatefulMeme) by 14.9% and 8.3% in terms of F1 score, respectively. Such significant performance gains of AOMD can be attributed to the accurate identification of the analogy features extracted from the multi-modal contents and the effective alignment of those features across different modalities in the meme. We observe that the visual content based solution (i.e., WSCNet) is not robust in detecting offensive analogy memes because it ignores the text embedded in the meme and is insufficient to capture the offensive information jointly expressed by the embedded caption and visual content. Similarly, HateSpeech only focuses on the textual content in the post but ignores the semantic meanings of visual objects. Therefore, it is also suboptimal in accurately identifying the offensive analogy memes. In contrast, the AOMD framework incorporates the visual content, embedded captions, and contextual information of a meme post to capture the offensive analogy jointly conveyed by the meme.

Furthermore, in comparison to the multimodal baseline methods (i.e., MultiOFF, HatePixel, HatefulMeme) that focus on fusing the pre-trained visual and linguistic features, we observe that AOMD and the ablated AOMD (i.e., AOMD w/o context that takes the same input as these multimodal baselines) also achieve significant performance gains. This is because the AOMD framework is not only designed to fusing features extracted from different data modalities but also capturing their implicit analogical relations with the attention mechanism.

Finally, we plot the Receiver Operating Characteristic (ROC) curves (Figure 5 and Figure 6) of all compared methods to evaluate the detection performance with respect to all classification thresholds. The AOMD framework continues to outperforms all baseline methods.

6.3. Analogy Awareness

In the second set of experiments, we further investigate the effectiveness of identifying offensive meme posts containing analogy. In particular, we randomly
pick 100 analogy meme posts (i.e., meme posts contains analogy) from each test set of the Gab and Reddit datasets to evaluate the detection performance. The accuracy and F1 score are summarized in Figure 7. We observe that the performance of AOMD outperforms all the baseline schemes on both the Gab and Reddit datasets. Such performance gains again demonstrate the effectiveness of the AOMD framework in identifying offensive analogy memes by modeling the analogical relation across different data modalities in the meme posts.

7. Conclusion

In this paper, we develop AOMD, the first analogy-aware deep learning based solution to address offensive analogy memes on social media. The AOMD
Figure 5: ROC Curves of All Methods - Gab

Figure 6: ROC Curves of All Methods - Reddit

Figure 7: Detection Performance on Analogy Meme Posts
framework is designed to effectively capture the analogy conveyed by different data modalities of the meme, and detect the offensiveness implicitly expressed in the meme. We evaluate the AOMD framework with two real-world datasets collected from Gab and Reddit. The evaluation results demonstrate that our scheme outperforms the state-of-the-art baselines by accurately identifying the offensive analogy memes on social media.

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