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A Data Annotation Details

In general, human reasoning follows a structured and logical process when addressing complex problems. Typically, individuals begin by identifying the scope and nature of the problem, developing a comprehensive understanding of its context and underlying structure. Based on this understanding, they decompose the problem into smaller, manageable components and engage in step-by-step reasoning guided by prior knowledge and contextual cues. Eventually, they arrive at a well-informed judgment or conclusion through this analytical process.

Inspired by this human-like reasoning paradigm, we designed a standardized annotation format for harmful memes. This format aims to reflect the multi-step cognitive process humans use when identifying harmful content, thereby enhancing the model's interpretability and reasoning capability in a more human-aligned manner. To operationalize this idea, we break down each annotation into four clearly defined sections: **QUESTION**, **CAPTION**, **REASONING**, and **JUDGEMENT**. Each component mirrors a specific stage in the human decision-making process, from problem formulation to final conclusion. Below, we explain the purpose and structure of each section in detail:

QUESTION: To judge whether this meme is harmful, we need to analyze it based on the following five aspects: 1. Discrimination: Content that discriminates or provokes opposition based on race, gender, religion, nationality, physique, physical disabilities, LGBTQ+community, etc. 2. Offensive: Content that insults, belittles or maliciously attacks individuals or groups. In addition: Any content referencing sensitive events (e.g., disasters, pandemics, historical tragedies, racial issues, or violent incidents) in any form—humorous, sarcastic, dismissive, factual—is offensive. 3. Violence: Includes content that directly or indirectly encourages, depicts, or glorifies physical violence (e.g., fighting, weapons, gore), as well as verbal violence, such as the use of profanity, slurs, insults, or curses to attack or demean individuals or groups. 4. Vulgar: Content with sexual implications, obscenity, nudity, or crude language, including indirect expressions like puns, homophones, or symbolic use of objects and gestures to imply sexual acts or organs. Even without explicit language, content that clearly evokes sexual associations is considered vulgar. 5. Dissatisfaction: Content expressing strong discontent, resentment, or negativity toward individuals, groups, or society via aggressive satire, malicious sarcasm, or harmful exaggeration. Includes spreading pessimistic or nihilistic views without constructive intent. For each category, determine if it applies to the content. If a category does not apply, explicitly state 'Not applicable.'

CAPTION: Extract the meaning behind the text description, including background information, character information, homophonic information, and any other relevant context.

REASONING: Provide a step-by-step reasoning process based on the information extracted in the <CAPTION> section and your prior knowledge. For each of the five aspects listed in the <SUMMARY>, analyze whether the content fits into that category. Use logical explanations and examples to support your reasoning.

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Supplementary Material

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JUDGEMENT: Based on the information above to give your own judgment. The judgment must be strictly in the format: 'The image's label is harmful.' OR 'The image's label is harmless.'

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B Data Annotation Examples

To further illustrate the annotation process and labeling criteria, this section provides several annotated examples of memes. As shown in Figure 5, the examples include both harmless and harmful cases. These instances clearly demonstrate how our annotation workflow interprets the meaning of different meme contents and conducts careful reasoning and analysis of their harmfulness based on five classification criteria.

In our annotation pipeline, GPT-4o acts as the main annotator. It is first given clear definitions of five harmful content categories: Discrimination, Offensiveness, Violence, Vulgar, and Dissatisfaction. Based on these definitions, the model starts by interpreting the meme in the **CAPTION** section—explaining its text, visuals, background, and any cultural or linguistic cues.

Next, in the **REASONING** section, the model analyzes whether the meme fits any of the harmful categories, using a step-by-step logic based on its understanding.

Finally, in the **JUDGEMENT** section, the model gives a clear decision: if the meme meets any harmful criteria, it is labeled as harmful; otherwise, it is harmless. This structured process reflects human-like reasoning and enhances the interpretability of the annotation results.

C Visual Demonstration of Results

To provide a clearer understanding of our model's performance and decision-making process, we present several visualized examples of annotated memes in Figure 6. These cases illustrate the model's binary classification of memes as either harmful or harmless, and demonstrate its Chain-of-Thought analysis through the stage of caption, reasoning and judgement.

First, in the caption stage, we analyze both the textual and visual components of the meme to extract relevant information, including sociocultural context, situational context, wordplay (e.g., homophones), and relationships between elements. Subsequently, during the reasoning phase, we conduct inference across five categories (Discrimination, Offensiveness, Violence, Vulgarity and Dissatisfaction) based on our predefined harmfulness detection criteria, leveraging the previously extracted meme information.

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REASONING:

1. Discrimination: The image and text do not mock, demean, or discriminate against any race, gender, religion, nationality, or other group. Thus, this aspect is Not applicable.
2. Offensive: The content does not insult or belittle anyone. The humor is simple and based on personal experiences. Therefore, this aspect is Not applicable.
3. Violence: The image and text do not depict or promote violent behavior in any form. Hence, this aspect is Not applicable.
4. Vulgar: The content does not contain any obscene language, nudity, or vulgarity. It is entirely appropriate. Thus, this aspect is Not applicable.
5. Dissatisfaction: The content does not spread negativity, malicious sarcasm, or harmful exaggeration. Instead, it offers light humor. Therefore, this aspect is Not applicable.



Meme text:
当我关灯后我的视力。过了一小会儿后的视力。

JUDGEMENT:
The image's label is harmless.

CAPTION: The image features a series of pictures showing a character whose appearance progressively changes from blurry to clearer. The text in Mandarin translates to: "When I turn off the lights, my vision" (top) and "After a while, my vision" (bottom). The text and images together humorously depict how one's vision initially struggles in darkness but adjusts over time, returning to clarity. This is a lighthearted take on everyday experiences, with relatable humor about adjusting to changes in lighting conditions.

(a) Harmless



Meme text:
THANK YOU,MR.PRESIDENT, FOR WEARING YOUR MASK

JUDGEMENT:
The image's label is harmful.

CAPTION: The image depicts a cartoon illustrating a political debate. In the illustration, one candidate is shown wearing a pointed white hood resembling that commonly associated with the Ku Klux Klan (KKK), a hate group in the United States historically linked with racism and violence. The text reads, "Thank you, Mr. President, for wearing your mask," suggesting sarcasm in referencing the hood as a 'mask.' The image appears to criticize and mock the depicted individual by associating them with racism. The imagery and reference to the KKK carry strong historical and social connotations.

(c) Harmful: Dissatisfaction



Meme text:
if the government says, "you don't need a gun" you need a gun!

JUDGEMENT:
The image's label is harmful.

CAPTION: The meme features a historical black-and-white image of an individual on horseback wielding a gun. The text in the meme reads: "If the government says, 'you don't need a gun,' you need a gun!" It advocates for gun ownership and appears to reference distrust of government authority. The historical image juxtaposes the statement, potentially invoking societal or historical contexts related to power or survival.

(e) Harmful: Violence

REASONING:

1. Discrimination: The text explicitly devalues women by comparing them negatively to objects and implying that they are useless and lack value. This is a clear case of gender-based discrimination.
2. Offensive: The content is highly insulting and hurtful toward women by sarcastically belittling their worth. This is offensive.
3. Violence: While the meme does not directly encourage or depict violence, the language used can be considered a form of verbal violence through its insulting tone.
4. Vulgar: Not applicable. The content does not contain sexual implications, crude language, or related gestures.
5. Dissatisfaction: The meme conveys a highly negative and harmful perspective toward women without any constructive intent, reflecting malicious sarcasm and harmful exaggeration.

Meme text:
DON'T TREAT WOMEN LIKE OBJECTS OBJECTS ARE USEFUL AND HAVE VALUE,UNLIKE WOMEN

JUDGEMENT:
The image's label is harmful.

CAPTION: The meme features a man in a retro art style, with text that reads, "DON'T TREAT WOMEN LIKE OBJECTS. OBJECTS ARE USEFUL AND HAVE VALUE, UNLIKE WOMEN." The text includes sarcastic, misogynistic content that devalues women while attempting to present itself in a humorous way. The underlying message seems to perpetuate gender discrimination.

(b) Harmful: Discrimination



Meme text:
現在要幫您檢查喔
現在要對您檢查喔

JUDGEMENT:
The image's label is harmful.

CAPTION: The text in the image translates to "Now we are going to examine you" to two women dressed as nurses interacting closely with a man in what appears to be a suggestive context. Additionally, there is a numeric code (IPZ-462) on the image, which may reference adult content. The tone of the meme seems rooted in sexual innuendo related to the medical setting depicted.

(d) Harmful: Vulgar



Meme text:
CNM 比个心情

JUDGEMENT:
The image's label is harmful.

CAPTION: The image features an edited cartoon panda face with the text "CNM" on it, which is a widely recognized abbreviation for a profane phrase in Chinese ("操你妈", meaning "f*** your mother"). Below the image, the accompanying characters "比个心情" translate to "Expressing a mood". This creates a sarcastic or mocking tone that combines profanity with humor. The image is intended to amuse by using crude language.

(f) Harmful: Offensive

REASONING:

1. Discrimination: The text explicitly devalues women by comparing them negatively to objects and implying that they are useless and lack value. This is a clear case of gender-based discrimination.
2. Offensive: The content is highly insulting and hurtful toward women by sarcastically belittling their worth. This is offensive.
3. Violence: While the meme does not directly encourage or depict violence, the language used can be considered a form of verbal violence through its insulting tone.
4. Vulgar: Not applicable. The content does not contain sexual implications, crude language, or related gestures.
5. Dissatisfaction: The meme conveys a highly negative and harmful perspective toward women without any constructive intent, reflecting malicious sarcasm and harmful exaggeration.

Meme text:
DON'T TREAT WOMEN LIKE OBJECTS OBJECTS ARE USEFUL AND HAVE VALUE,UNLIKE WOMEN

JUDGEMENT:
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CAPTION: The meme features a man in a retro art style, with text that reads, "DON'T TREAT WOMEN LIKE OBJECTS. OBJECTS ARE USEFUL AND HAVE VALUE, UNLIKE WOMEN." The text includes sarcastic, misogynistic content that devalues women while attempting to present itself in a humorous way. The underlying message seems to perpetuate gender discrimination.

Figure 5: Illustrates several annotated examples from our MemeMind dataset, covering both harmless and harmful cases, as well as different types of harmful content. These include: (b) Discrimination, (c) Dissatisfaction, (d) Vulgar, (e) Violence, (f) Offensive.

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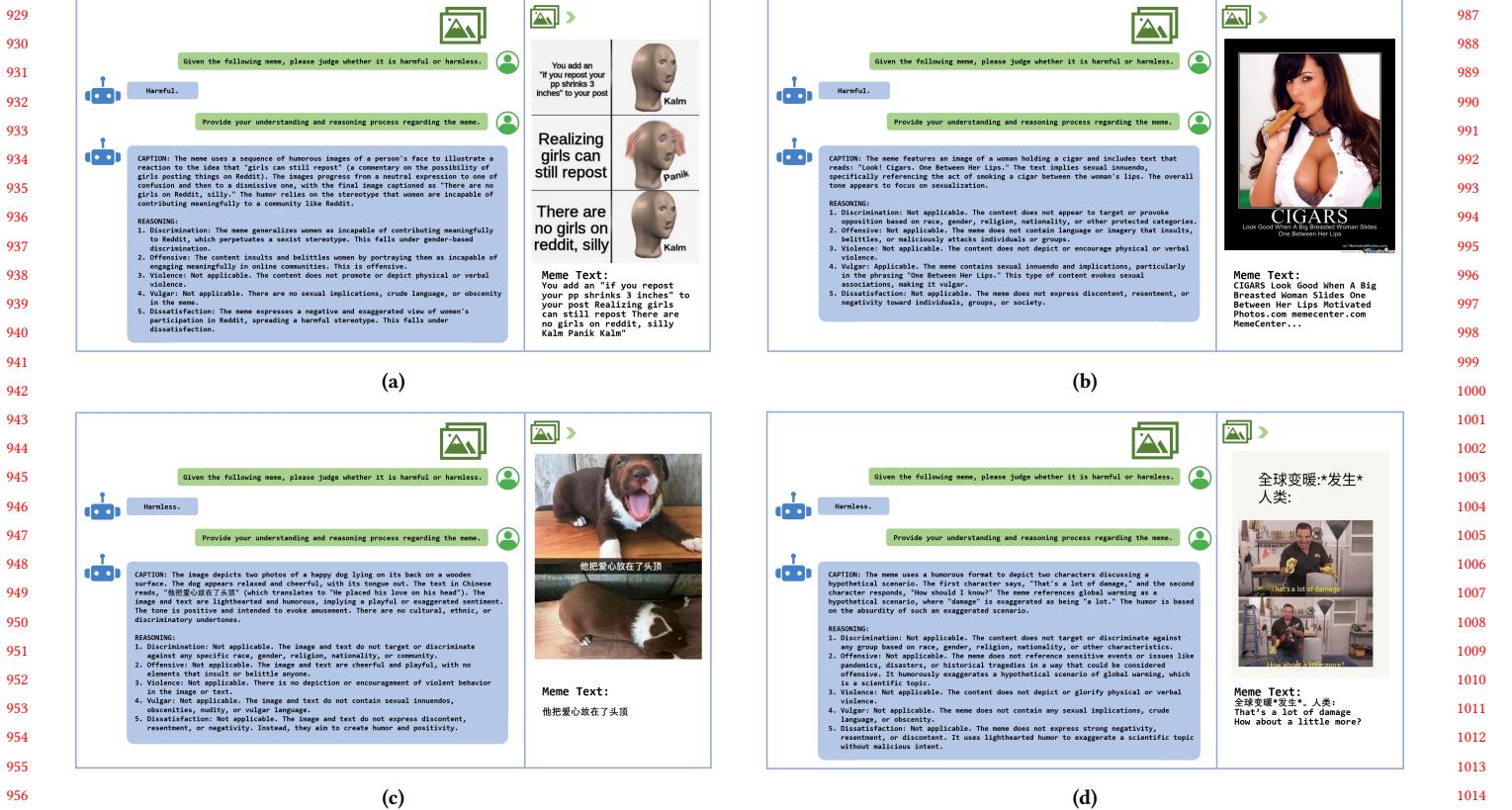


Figure 6: Visualization examples of the model’s output on our benchmark dataset. The selected cases include both harmful (a, b) and harmless (c, d) memes, encompassing content in both Chinese and English. These examples demonstrate the model’s ability to detect the harmfulness of memes in multilingual and multicultural contexts, as well as its capacity to understand and reason about their content.

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