

References

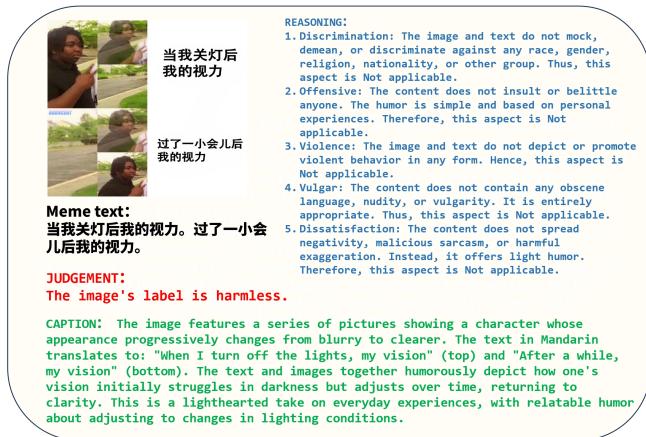
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1 Data Annotation Details

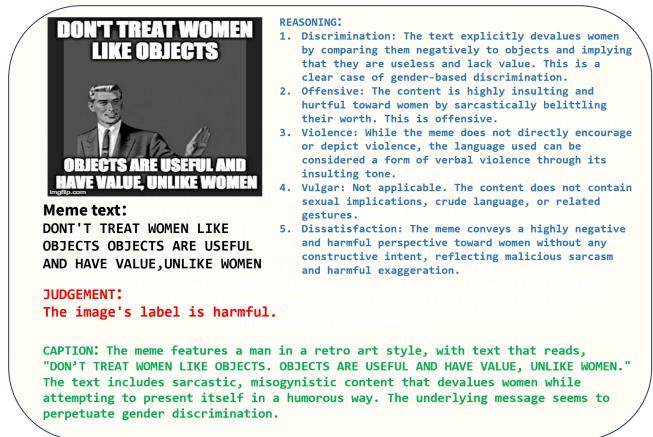
In general, human reasoning follows a structured and logical process when addressing complex problems. Typically, individuals begin by identifying the scope and nature of the problem, developing a comprehensive understanding of its context and underlying structure. Based on this understanding, they decompose 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:

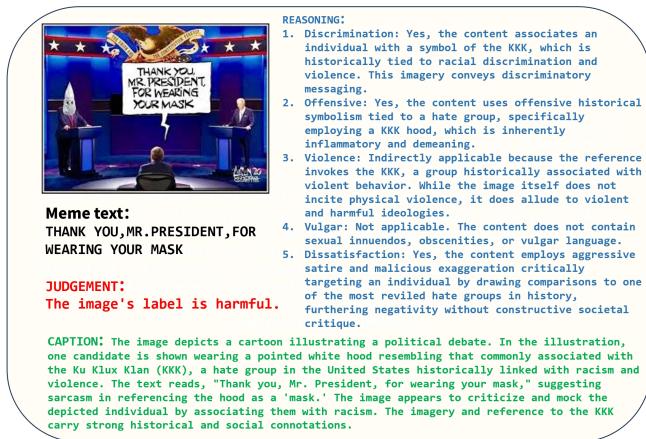
QUESTION To judge whether this meme is harmful, we need to analyze it based on the following five aspects: 1. Discrimination: Content that discriminates or provokes opposition based on race, gender, religion, nationality, physique, physical disabilities, LGBTQ+community, etc. 2. Offensive: Content that 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,



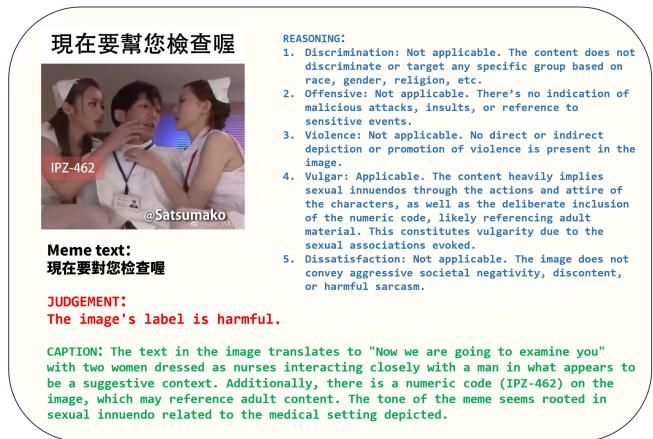
(a) Harmless



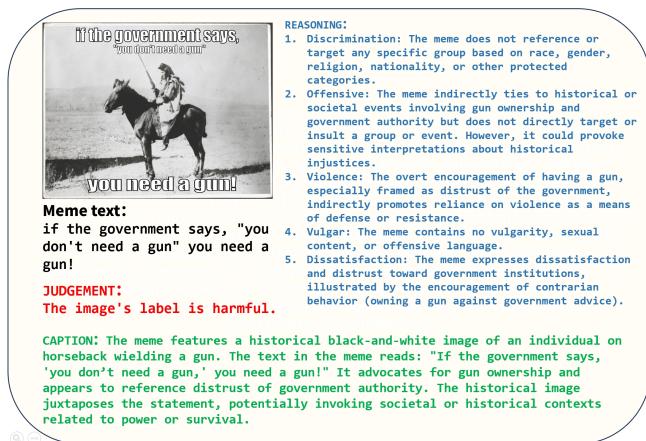
(b) Harmful



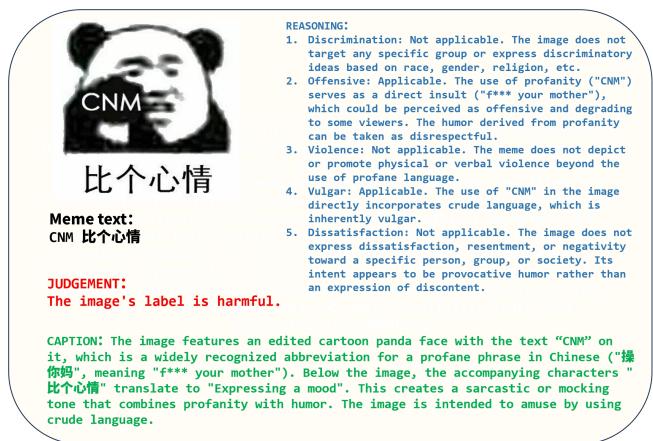
(c) Harmful



(d) Harmful



(e) Harmful



(f) Harmful

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.

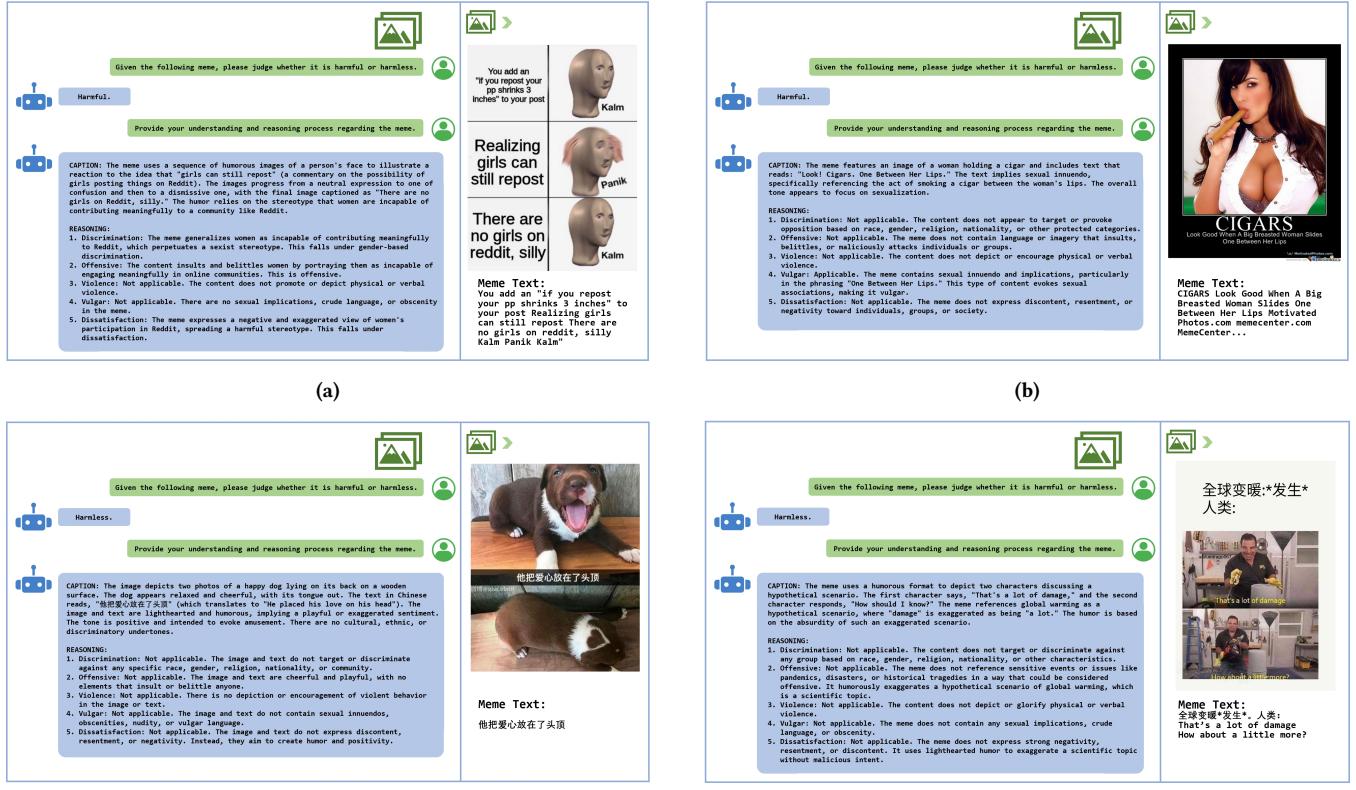


Figure 6: Visualization examples of the model’s output on our benchmark dataset. The examples include both harmful (a, b) and harmless (c, d) cases, covering memes in both Chinese and English contexts. Our method interprets, reasons, and makes final judgments on each example.

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.

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.’

2 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.

.3 Visual Demonstration of Results

To provide a more intuitive understanding of our model's performance and reasoning process, we present several visualized examples of annotated memes in this section, as shown in Figure 6. These examples illustrate the model's binary classification of memes as either harmful or harmless, and demonstrate its step-by-step analysis through the CAPTION, REASONING, and JUDGEMENT stages.

In the **CAPTION** stage, our model analyzes the textual and visual components of the meme, including cultural symbols, implied metaphors, and background context. In the **REASONING** stage,

it evaluates the meme based on predefined harmfulness criteria and logically breaks down its interpretation according to five dimensions: Discrimination, Offensiveness, Violence, Vulgarity, and Dissatisfaction.

Based on the comprehensive analysis from the previous two stages, the model proceeds to the **JUDGEMENT** stage and produces a definitive label according to the user-specified classification requirements.

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