Findings of the CONSTRAINT 2022 Shared Task on Detecting the Hero, the Villain, and the Victim in Memes

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Abstract

We present the findings of the shared task at the CONSTRAINT 2022 workshop on “Hero, Villain, and Victim: Dissecting Harmful Memes for Semantic Role Labeling of Entities.” The task aims to delve deeper into meme comprehension by deciphering the connotations behind the entities present in a meme. In more nuanced terms, the shared task focuses on determining the victimizing, glorifying, and vilifying intentions embedded in meme entities to explicate their connotations. To this end, we curate HVVMemes, a novel meme dataset of about 7,000 memes spanning the domains of COVID-19 and US Politics, each containing entities and their associated roles: hero, villain, victim, or other. The shared task attracted 105 registered participants, but eventually only nine of them made official submissions. The most successful systems used ensembles combining textual and multimodal models, with the best system achieving an F1-score of 58.67.

1 Introduction

The unwarranted spread of misinformation (Wu et al., 2019; Hardalov et al., 2022), propaganda (Da San Martino et al., 2020a,b), fake news (Lazer et al., 2018; Vosoughi et al., 2018), COVID-19 info-  
demic (Alam et al., 2021b; Nakov et al., 2022), hate speech (MacAvaney et al., 2019; Zampieri et al., 2019a), and other harmful content (Nakov et al., 2021) has plagued social media. Lately, memes have emerged as a powerful multimodal means to disseminate malicious content due to their ability to circumvent censorship norms (Mina, 2014) and to their fast-spreading nature. With an aptly crafted combination of images and text, a seemingly naïve meme can easily become a source of harmful information diffusion. As a result, exploring the noxious side of memes has become a pressing research topic; see also recent surveys on harmful memes (Sharma et al., 2022b) and on multimodal disinformation detection (Alam et al., 2021a).

While meme analysis has been studied in a variety of contexts, such as hate speech (Zhou et al., 2021; Kiela et al., 2020) harmfulness (Pramanick et al., 2021a,b), emotions (Sharma et al., 2020), misinformation (Zidani and Moran, 2021), sarcasm (Kumar and Garg, 2019), offensiveness (Suryawanshi et al., 2020), and propaganda (Dimitrov et al., 2021a,b), limited forays have been made on comprehending the role of the entities that make up a meme. This is our main focus here: on identifying the hero, the villain, and the victim entities present in a meme. Given a meme and a list of the entities it involves, the task is to identify which entity plays what role. Such categorization of the entities in the meme can help understand the entity-specific connotation and their nature, attitudes, decisions, and demeanour. For instance, when the meme creators intend to spread misinformation and hatred towards minority communities or to defame certain individuals, politicians, or organizations, they would depict the target entities as villains. Similarly, when the intent is to shed light on the deplorable state of certain entities or to glorify them, these entities would be portrayed as victims or as heroes, respectively.

Fig. 1 depicts apt examples for hero, villain, and victim categorization of the entities in a meme. The meme in Fig. 1a draws a comparison between Abraham Lincoln, John F. Kennedy, and Donald Trump, where the former three are portrayed as heroes, while Donald Trump is shown in negative light, as a villain. Similarly, Fig. 1b mocks Jill Stein and the Green Party as villains for allegedly getting bribed by the rich. Fig. 1c on the other hand, frames the Republican Party as a villain, for their inconsiderate views on the poor, the minorities, and women, thus making them the victims. In conclusion, through depictions of heroism, villainy, and victimization, memes act as an appealing means to propagate certain views about the targeted entities.
While some previous meme studies have sought to identify harmfulness and the entities (Sharma et al., 2022a) or the categories that are being targeted, e.g., a person, a group, an organization, or society (Pramanick et al., 2021a,b), none of them has scrutinized the entity’s connotation. Our shared task aims to bridge this gap. We release HVVMemes, a meme dataset with about 7,000 memes on COVID-19 and US Politics, where each meme is annotated with a list of entities, each labeled with its role: hero, villain, victim, or other. The shared task attracted 105 teams, and nine of them made official submissions. Most teams fine-tuned pre-trained language and multimodal models or used ensembles, with the best system achieving an F1-score of 58.67. We discuss the submissions and their approaches in more detail in Section 5.

Despite the growing body of research on meme analysis, understanding the connotation underlying the individual entities in the meme remains a challenging endeavour. Their camouflaged semantics, satirical outlook, and cryptic nature make their analysis a daunting task (Sabat et al., 2019). Moreover, categorizing the entities as heroes, villains, or victims requires real-world and commonsense knowledge, which often are not present in popular pre-trained language models. Thus, it should not be surprising that, as the shared task’s results show, off-the-shelf multimodal models, as well as various ensembles thereof, struggle with this task (Kiela et al., 2020). This highlights that the current state-of-the-art visual-linguistic models are unable to grasp the veiled information present in the memes. Thus, we hope that the dataset and task will foster further research in this interesting direction.

More details about the shared task is available at http://constraint-lcs2.github.io/
Additional contextual cues involving commonsense knowledge (Shang et al., 2021), semantic entities, cues about the protected categories (Pramanick et al., 2021b; Karkkainen and Joo, 2021), along with other meta information, have also been explored for characterising various aspects of the online harm conveyed by memes. Most such tasks address affect detection at various levels of granularity, sometimes organised in a taxonomy. Still, none of these tasks has focused on explicitly modeling the complex narrative framework of the memetic discourse surrounding the specific entities referred to in the meme. With this in mind, here we attempt to alleviate a few associated challenges by exploring the feasibility of entity-specific visual-semantic role labelling for memes.

Other Related Shared Tasks. Several shared tasks have targeted the broad field of harmful social media content. Some tasks investigated the characterisation of offensive language, hate speech, profanity, and associated fine-grained attributes such as implicit and explicit implications in binary, multi-class, multi-label, and hierarchical settings (Struš et al., 2019; Zampieri et al., 2019b, 2020). Their coverage has been fairly comprehensive in terms of the languages covered including Arabic, Danish, Greek, English, Turkish, and Dravidian Languages like Tamil, Malayalam, Kannada as well as German and English/Indo-Aryan code-mixing (Zampieri et al., 2019b; Mubarak et al., 2020; Zampieri et al., 2020; Chakravarthi et al., 2021; Modha et al., 2021). They also address harmful content dissemination, targeting various protected categories such as religious affiliation, national origin, sex, etc. (Zhang et al., 2019). Other efforts have targeted misinformation, propaganda, and persuasiveness detection (Aly et al., 2021; Shaar et al., 2021; Da San Martino et al., 2020a), where the goal is to detect verifiable claims, their veracity, span, and check-worthiness. Persuasive technique detection has also been explored for images besides text-based content, e.g., Dimitrov et al. (2021b) introduced the task of propaganda in memes.

Some tasks have attempted to address affect concerning various targets. Xu et al. (2016) focused on stance prediction for given targets, i.e., whether the comment is in favour or against the target, both in supervised and in unsupervised scenarios. Molla and Joshi (2019) modeled sarcastic targeting of specific entities. Rosenthal et al. (2017) focused on sentiment analysis in Twitter.

| Domain | Splits | # Memes | # Referenced Entities |
|--------|--------|---------|-----------------------|
|        |        |         | Hero | Villain | Victim | Other | Total |
| COVID-19 | Train | 2,700  | 163  | 576  | 317  | 2,438 | 3,494 |
|         | Val    | 300    | 19   | 65   | 40   | 268   | 392   |
|         | Test   | 381    | 18   | 106  | 50   | 359   | 533   |
|         | Total  | 3,381  | 260  | 747  | 407  | 3,065 | 4,419 |
| Politics| Train  | 2,852  | 230  | 1,308 | 441  | 2,617 | 4,596 |
|        | Val    | 350    | 27   | 166  | 58   | 317   | 568   |
|        | Test   | 350    | 31   | 167  | 45   | 308   | 551   |
|         | Total  | 3,552  | 288  | 1,641 | 544  | 3,242 | 5,715 |

Table 1: Statistics about our HVVMemes dataset.

In contrast, here we focus not only on the polarity of the target entity, but also on understanding complex connotations such as glorification, vilification, and victimisation in memes. This is both challenging and important, as memetic discourse has taken over a sizable portion of online engagement and as it requires specialised moderation given its multimodal nature.

3 Dataset Curation

Towards curating a dataset that would enable the identification of hero, villain, and victim as roles in memes, we leveraged and reannotated the HarMeme dataset released in (Pramanick et al., 2021b), and we call this new dataset HVVMemes. HarMeme includes 3,544 memes about COVID-19 and 3,552 memes about US Politics, which are annotated for harmfulness as well as for target type, in case the meme is harmful, with four categories for the latter: individual, organisation, community, and society. Table 1 gives some statistics about HVVMemes (note that for COVID-19, we filtered out some of the memes in HarMeme, keeping 3,381 of the original 3,554 memes). As a general trend for both domains, we observe a neutral reference for most of the entities mentioned in the memes (3,065 for COVID-19, and 3,242 for US Politics); for such cases, we assign a fourth category: other. We further see that villain is the second most frequent role (747 memes for COVID-19, and 1,641 for US Politics), followed by victim (407 memes for COVID-19, and 544 for US Politics), and then hero (200 memes for COVID-19, and 288 for US Politics). We believe that this is a realistic representation of social media engagement involving memes, which are mostly humorous with neutral connotations, and less frequently harmful by indulging in vilification. Victimisation can also be interpreted as a countering resistance to incessant vilification. Finally, glorification is generally the weakest voice in memetic discourse.

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Table 2: Key considerations in our annotation guidelines.

| S. No. | Annotation Guidelines |
|--------|-----------------------|
| 1      | Meme author’s perspective needs to be considered as the frame of reference, while assigning roles. |
| 2      | Towards complete assimilation, both visual and textual cues should be factored in. |
| 3      | Relevant background context should be acquired before assigning roles. |
| 4      | Ambiguous memes can be categorised as other. |
| 5      | A 3-point Likert scale based mental frame of reference, implying negative, neutral and positive sentiments involved, should steer the connotation adjudication. |
| 6      | All reasonably intelligible (without ambiguity) entities that are referred to in the meme must be considered as valid targets. |
| 7      | Entities with multiple interpretations should be categorised as other. |
| 8      | The role of the original speaker of a quote, as expressed within a meme, must not be presumed. |

Table 3: Examples of resolution remarks that we provided to the annotators towards entity identification.

| Entity | Resolution Remark |
|--------|-------------------|
| Corona | resolved to Corona Beer (whenever valid). |
| Govt.  | resolved to Government. |
| Putin  | resolved to Vladimir Putin. |
| CDC    | standardised as Centre of Disease Control (CDC). |

3.1 Annotation Setup

Since entity role labelling is complex and subjective, we formulated clear annotation guidelines, which are summarized in Table 2. Each meme was annotated by three annotators, and the disagreements were resolved with the help of a consolidator. We asked the annotators (i) to identify the entities, and (ii) to assign roles to these entities.

3.1.1 Identifying the Entities

This step requires the annotators to elicit all entities that the meme refers to. This includes persons, norp (nationalities, religious, or political groups), facilities, organizations, geopolitical entities, locations, products, and other, as defined by spaCy’s label scheme for named entity recognition. \(^1\)

\(^1\)spacy.io/models/en#en_core_web_sm

To assist the annotators, we provided them an exhaustive list of all automatically identified entities along with resolution remarks whenever needed as shown in Table 3. Note that the annotators were not restricted to select entities from our provided list, which can be error-prone as automatic named entity recognition is not perfect; in fact, they were encouraged to add additional entities as needed, e.g., such shown in the image, but not mentioned in the textual part of the meme.

Fig. 2a shows a word cloud visualization of the entities referenced in COVID-19 memes: we can see social, global, political, and economic entities such as coronavirus, China, home, Wuhan, mask, work, etc. Similarly, in Fig. 2b shows a word cloud for US Politics memes, where we see entities like Biden, party, Donald, Democratic, Obama, etc.

(a) COVID-19  
(b) US Politics

Figure 2: Word clouds for (a) COVID-19 and (b) US Politics domains in HVVMemes.
To assess the general agreement between the annotators, we considered an agreement towards entity identification if at least two annotators agreed on an entity in the meme. The number of memes with agreed entities was normalised by the total number of memes with at least one valid entity assignment by the annotators. This was done independently of the implied role category, as the emphasis in this first step is on entity identification. The highest agreement towards this was 0.98, which suggests the reliability associated with the annotator’s collective understanding of the task. We followed a similar approach for the overall role-wise inter-annotator agreement; see below.

### 3.1.2 Role Assignment

The annotation was done in three stages: (i) dry-run, (ii) complete annotation, and (iii) consolidation. As part of the dry-run, the annotators and the consolidator annotated a random subset of 250 memes, assigning the entities the roles of hero, villain, victim, and other. Then, we gave them feedback and we trained them carefully by issuing detailed guidelines that included the formal definitions of the role categories and the instructions exemplifying the edge scenarios identified as part of the dry-run disagreements. In the second stage, the annotators performed a complete annotation. This was followed by a third consolidation stage with the help of a consolidator.

Due to the varying annotation responses and coreferencing for each role, conventional annotation agreement measures are not suitable for our setup. We consider an agreement when at least two annotators agree on one of the candidate entities for a particular role, which we formalize as the following role-wise agreement score $a$:

$$a = \frac{v_{agr}}{v_{tot}} \quad (1)$$

We define $v_{agr}$, which refers to the total number of valid agreements, and $v_{tot}$, which is the total number of valid responses, as follows:

$$v_{agr} = \sum_{i=1}^{N} I_i; \quad v_{tot} = \sum_{i=1}^{N} Z_i \quad (2)$$

where $I_i$ is a valid agreement (1, iff two or more annotators agree on an entity in example $i$), $Z_i$ is a valid response (1, iff at least one annotator provides a valid entity as a response in example $i$), and $N$ is the total number of examples in the dataset.

| Roles   | Covid-19 (Stage-2) | Covid-19 (Stage-3) | US Politics (Stage-2) | US Politics (Stage-3) | Avg. (Stage-3) |
|---------|--------------------|--------------------|-----------------------|-----------------------|---------------|
| Hero    | 0.30               | 0.54               | 0.36                  | 0.51                  | 0.53          |
| Villain | 0.31               | 0.55               | 0.55                  | 0.73                  | 0.64          |
| Victim  | 0.21               | 0.55               | 0.24                  | 0.43                  | 0.49          |
| Other   | 0.58               | 0.68               | 0.76                  | 0.88                  | 0.78          |
| Avg.    | 0.35               | 0.58               | 0.48                  | 0.64                  | 0.61          |

Table 4: Inter-annotator agreement (IAA) summary for completed (Stage-2) and consolidated (Stage-3) stages of the annotation process. Note that the average IAA for the dry-run (Stage-1), for COVID-19 and US Politics combined, was 0.50 (hero), 0.35 (villain), 0.14 (victim), and 0.55 (other).

In the first dry-run stage of the annotation process, the annotators worked on 250 memes, and then we examined their agreement, which was 0.50, 0.35, 0.14, and 0.55, for the roles of hero, villain, victim, and other, respectively, for COVID-19 and US Politics combined. The inter-annotator agreement for stages 2 and 3 is shown in Table 4. We can see that the average agreement scores after the completion stage (stage-2) are 0.35 and 0.48 for COVID-19 and US Politics, respectively. After the consolidation stage (stage-3), these numbers increased to 0.58 and 0.64, respectively.

### 3.2 Role-wise Analysis of HVVMemes

The distribution of the referencing entities within our HVVMemes dataset is somewhat skewed towards specific entities as well as towards specific predominant roles for these specific entities. The entities fairly emulate the prevalent trends and discourse topics that social media engagement around the period of the dataset collection reflected, which was at the onset of the COVID-19 pandemic and the surrounding political outlook within the United States of America. We observed that entities like Donald Trump and China were referenced almost equally in COVID-19 memes as a villain and other, while other entities are invariably referenced as other using humor, sarcasm, limerick, etc. For the domain of US Politics, on one hand, entities like Donald Trump, the Democratic Party, the Republican Party, and the Democrats are observed to have similar trend of pre-dominantly being referenced as a villain and other, and on the other hand, as a general trend, most of the memes have at least one vilified reference.
## 4 Shared Task Details

The CONSTRANT 22 Shared Task on Detecting the Hero, Villain, and the Victim in Memes asked to predict which entities are glorified, vilified, and victimised in a given meme. We gave the participants the above-described labeled training and validation datasets, where for each meme, we had the list of corresponding entities and their labeled role. The task was, given a meme and a list of entities, to predict the role of each of these entities in the meme. We provided the data split by topic (COVID-19 and US Politics), as discussed in Section 3. For the test set, we combined and shuffled the memes from the two topics, and we provided the memes with a list of corresponding entities, but no labels.

The task was organized on CodaLab, an open-source platform widely used to host machine learning and data science competitions. Our competition link provided all the necessary resources for the participants including archived news, notifications, and forum posts communicated during the running of the competition. We allowed the participants a maximum of 25 submissions, and the best submission was considered for the leaderboard.

The official evaluation measure was macro-F1 score, as we have an imbalanced multi-class problem. We further report precision and recall.

### 5 Participation and Results

The total of 105 teams registered for the competition, and nine of them made submissions to the leaderboard, making a total of 71 attempts to improve their scores. The teams tried a variety of approaches, and below we discuss the approaches by the six teams who also submitted a system description paper with information about their runs.

| Rank | System          | Precision | Recall | F1    |
|------|-----------------|-----------|--------|-------|
| 1    | shiroe          | 55.76     | 62.73  | 58.67 |
| 2    | jayeshbankoti   | 53.58     | 59.45  | 56.01 |
| 3    | c1pher          | 53.91     | 57.25  | 55.24 |
| 4    | zhouziming      | 54.19     | 55.36  | 54.71 |
| 5    | smontariol      | 57.96     | 44.97  | 48.48 |
| 6    | jzl123001       | 47.98     | 44.97  | 46.18 |
| 7    | amanpriyanshu   | 30.98     | 34.35  | 31.94 |
| 8    | IIITDWD         | 25.57     | 23.79  | 23.86 |
| 9    | rabindra.nath   | 25.30     | 25.30  | 23.72 |

Table 5: Leaderboard summary for the shared task.

- **shiroe/jayeshbankoti** (Kun et al., 2022) achieved the best results overall. One of the distinctive approaches that the authors followed was making use of Celebrity face detection from the input meme images using Giphy’s Github. In addition, a sub-image detector using YoloV5 leveraged the bounding boxes for memes with multiple images. This was input into an ensemble model of DeBERTa (He et al., 2021) + RoBERTa (Liu et al., 2019) + ViLT (Kim et al., 2021) + EfficientNetB7 (Tan and Le, 2019) with averaging of the predictions in the final layer. Though they incorporated a celebrity detector, the lack of other external knowledge limited their system performance.

- **c1pher** (Singh et al., 2022) were ranked third. It is remarkable that they achieved this result using just the text input. They formulated the problem as a Multiple Choice Question Answering Task (MCQA), and they used an ensemble of three modules: twitter-xlm-roberta + COVID-BERT (Müller et al., 2020) + BERT-tweet (Nguyen et al., 2020). They further added a sentiment module trained using RoBERTa, with the final classification layer comprising Support Vector Machine (SVM). A major drawback of this approach is that they ignored the image as an input altogether.

- **zhouziming/jzl123001** (Zhou et al., 2022) leveraged the Visual Commonsense Reasoning (VCR) framework in a multimodal model. They built an ensemble of VisualBERT (Li et al., 2019) + UNITER (Chen et al., 2020) + OSCAR (Li et al., 2020) + ERNIE-Vil (Yu et al., 2021), combined using an SVM. To handle the disproportionately large number of Other examples, they introduced loss-reweighting. The lack of sufficient external knowledge and position information about the OCR text with the image restricted their system performance. Their source code is available at https://github.com/zjl123001/DD-TIG-Constraint

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2http://codalab.lisn.upsaclay.fr/competitions/906

3http://github.com/Giphy/celeb-detection-oss

4https://github.com/ultralytics/yolov5
Table 6: Models used by the participants as part of their system submissions. **R-BERT**: RoBERTa, **D-BERT**: DeBERTa, **EB7**: EfficientNetB7, **OFA**: Once-for-All, **ViLT**: Visual and Language Transformer, **ViT**: Visual Transformer, **VB**: Visual BERT, **U**: UNITER, **O**: OSCAR, **E-V**: ERNIE-Vil, **SVM**: Support Vector Machines, **XGB**: XGBoost, **BF**: Block Fusion and **W-P**: Wu-Palmer.

- **smontariol** (Montariol et al., 2022) experimented with sampling to handle data imbalance, trying six strategies. On top of that, they used an ensemble of CLIP (Radford et al., 2021) + VisualBERT + OFA (Cai et al., 2020) with XGBoost as the final layer for classification. The potential limitations of this approach include OCR errors and issues with image-text correspondence. Their source code is available at [https://github.com/smontariol/mmsrl_constraint](https://github.com/smontariol/mmsrl_constraint).

- **IIITDWD** (Fharook, 2022) combined sentiment- and lexicon-based approaches to associate sentiment polarity and roles with each entity. For sentiment classification, they used VADER[^5]. Moreover, to associate commonly used words for *hero*, *villain*, and *victim*, they developed a corpus and used Wu-Palmer similarity[^6]. The way was done and its impact are described in insufficient detail. Their source code is available at [https://github.com/fharookshaik/shared-task_constraint-2022](https://github.com/fharookshaik/shared-task_constraint-2022).

- **rabindra.nath** (Nandi et al., 2022) proposed an approach using BLOCK fusion (Benyounes et al., 2019) for combining the image with text embeddings. They used a combination of ViT (Bobicev and Sokolova, 2017) and BERT (Devlin et al., 2019) for the image and for the text, respectively, followed by SVM as the final layer for classification. The empirical approach limits their system performance despite adding several data augmentation techniques. Their source code is available at [https://github.com/robi56/harmful_memes_block_fusion](https://github.com/robi56/harmful_memes_block_fusion).

[^5]: [https://pypi.org/project/vaderSentiment/](https://pypi.org/project/vaderSentiment/)
[^6]: [https://arxiv.org/ftp/arxiv/papers/1310/1310.8059.pdf](https://arxiv.org/ftp/arxiv/papers/1310/1310.8059.pdf)

The evaluation results for the above systems are shown in Table 5. We can see that the macro-F1 scores range between 58.67 and 23.72, with a mean of 44.31 and a median of 48.48.

Table 6 further gives a summary of the most important components of the participating systems. We can see that one commonly used architecture is BERT and its variants, including multi-modal variants, whereas SVM is the preferred way to combine the components of ensemble systems.

6 Conclusion

Understanding and interpreting the connotations behind the entities in a meme is a difficult problem, which we pioneered in this shared task. Given a meme and a list of entities, the task asks to detect the role of each entity as a *hero*, *villain*, *victim*, or *other*. We curated HVVMemes, a large-scale meme dataset of 7,000 memes spanning the domains of COVID-19 and US Politics, annotated with the entities they refer to as well as with their role. The shared task attracted 105 registered participants, out of which nine made official submissions, and six submitted papers describing their systems. We hope that our dataset and task setup will enable further research towards understanding how entities are portrayed in memes.

Acknowledgments

The work was partially supported by a Wipro research grant, Ramanujan Fellowship, the Infosys Centre for AI, IIIT Delhi, and ihub-Anubhuti-iiitd Foundation, set up under the NM-ICPS scheme of the Department of Science and Technology, India. It is also part of the Tanbih mega-project, which is developed at the Qatar Computing Research Institute, HBKU, and aims to limit the impact of “fake news,” propaganda, and media bias by making users aware of what they are reading, thus promoting media literacy and critical thinking.
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