Arka Ujjal Dey, Artemis Llabrés, Ernest Valveny and Dimosthenis Karatzas Computer Vision Center, Universitat Autònoma de Barcelona, Spain

ABSTRACT

Social Media posts, where real images are unscrupulously reused along with provocative text to promote a particular idea, have been one of the major sources of disinformation. By design, these claims are without editorial oversight and accessible to a vast population who otherwise may not have access to multiple information sources. This implies the need to fact-check these posts and clearly explain which parts of the posts are fake. In the supervised learning setup, this is often reduced to a binary classification problem, neglecting all intermediate stages. Further, these claims often involve recent events on which systems trained on historical data are prone to fail. In this work, we propose a zero-shot approach by retrieving real-time web-scraped evidence from multiple news websites and matching them with the claim text and image using pretrained language vision systems. We propose a graph structured representation, which a) allows us to gather evidence automatically and b) helps generate interpretable results by explicitly pointing out which parts of the claim can not be verified. Our zero-shot method, with improved interpretability, generates competitive results against the state-of-the-art methods.

1 INTRODUCTION

Disinformation through Social Media posts can be characterized as retelling an existing story, usually with a visual aid. In the past, this visual aid usually consisted of some existing image being repurposed; thus, tracing the image to its real-world origin would have unmasked the truth. However, the danger of increasing realistic deepfakes means we can no longer use only vision modality for image similarity; instead, we should look at the source, too. This form of disinformation can be particularly dangerous because images are a powerful tool for propaganda, often evoking deep emotions. Further, the inclusion of images in Social media posts [12] leads to increased likes and shares, perpetuating a misleading sense of credibility. All this, coupled with the ease of image re-purposing and the fact that it does not require any technical knowledge or expertise, makes out-of-context usage of images a major source of disinformation. We understand Out-of-context usage as the purposeful misuse of the image by changing its context. However, given that the purpose is misuse, the most harmful choices for re-purposing are images that are already rich with visual information rather than generic or symbolic. These are also the kinds of images that are often reported in news media. Thus, we propose a framework for verifying social media posts against news websites in this work.

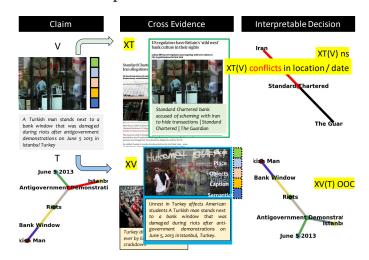


Figure 1: Core Idea: Fact-checking Social Media Posts against News Websites: Example of an image-text claim where the image has been used out-of-context. XV(T) is Visual cross-evidence from text claim T, and XT(V) is Text cross-evidence from image claim V. We show through a graph-based text representation that 'riots' and 'June 5 2013', among others, are supported by the XV(T) through similarly colored nodes and edges. However, the retrieved image is not visually similar to the original one, and thus, this is judged as Out-of-Context (OOC). Furthermore, XT(V) does not support T in terms of matched nodes or edges but instead conflicts regarding the location context ("Turkey' vs. 'Iran').

Out-of-context detection has been addressed in the past as a learning task. However, gathering large-scale labeled out-of-context datasets takes time and effort. Previous efforts at creating synthetic datasets were focused on swapping captions [7] or replacing entities [17] and generating pseudo-fakes. In [13], we see the use of a language vision system to create synthetic fakes by mapping news clip images to semantically similar but unrelated (in reality) captions. The authors observed that machine-driven image re-purposing is now a realistic threat and provided samples that represent challenging instances of mismatch between text and image in news that can mislead humans. This was followed up in [19], where further automated manipulations were introduced through complete swaps or

slight attribute changes, creating a further realistic out-of-context dataset.

The image-text pairs are so convincing that they should no longer be judged in isolation but only through support from external knowledge, almost like how journalists fact-check news by looking for supporting or contesting evidence. In [1], we see our inspiring idea, where the authors use automatically web-scraped external evidence to detect OOC usage of image-text. The authors introduce the idea of cross-evidence to fact-check multi-modal posts, where the image is reverse searched to find evidence text, and text is searched to find evidence image. However, the underlying issue that needs to be addressed is how the style of the text (claim) biases the results (evidence) it returns. When a story is retold subjectively in social media, it loses the style of the source (news website), affecting the retrieval of relevant evidence from direct searches.

In our work, we rely on this idea of OOC detection through external evidence but try to overcome the main limitations of previous approaches, which can be summarized in the following points:

- Learning-based approaches need for labeled data, which is difficult to obtain, and synthetic datasets often don't capture the distribution of actual fake news.
- Black box binary classification often renders the final output opaque. This is particularly relevant for fact-checking, where explaining is often as crucial as prediction.
- Fact checking relies on the retrieval of good evidence, which
 is often affected adversely by claim visual quality and text
 style.

Therefore, in this work, we explore zero-shot rule-based matching as an alternative to data-driven learning of fake versus real claims. This zero-shot approach is interpretable by design and, therefore, enriches the final decision with explainability. Furthermore, we introduce a feedback-based retrieval of evidence that iteratively improves the search results.

In summary, our main contributions are:

- We propose a Structured Representation of Text in terms of LLM-aided Entity Relationship graphs and Pretrained Visual Features that allow us to do rule-based matching against data-driven learning for Out-of-context Detection
- We propose a Feedback-based Retrieval that iteratively improves upon search results by leveraging our structured representation and exploring unmatched nodes. This retrieval is aided by an LLM
- We propose a Zero-shot Verification and Explanation scheme that applies strict matching rules to the structured representations of the claim and evidence to generate interpretable results.

2 RELATED WORKS

In this section, we look at the related work in terms of 1) fact-finding or evidence retrieval strategies, 2) the supervision used to learn, 3) the explanations, if any provided, as part of the reasoning, and finally, 4) the bias in the designs of the task and dataset.

Several works study the detection of multi-modal misinformation [1, 2, 8, 9, 13]. Some of them deal with a small scale human-generated multi-modal fake news [8, 9], while others address out-of-context misinformation where a real image can be paired with a

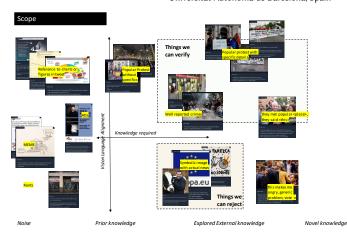


Figure 2: Scope: Fact checking Social Media Posts against News Websites

swapped real text often with manipulated textual and location data as in [17] or even without any manipulation [1, 2, 13].

2.1 Retrieval Based Reasoning

The use of external evidence has been explored in Vision Language tasks, but mostly related to Visual Question Answering [10, 14, 20] leveraging publicly available external knowledge bases. In the case of VQA, primarily it is the question words [14] along with visual cues in the form of scene labels [14], detected entities [10], or predicted visual attributes [20], that are used to retrieve knowledge from external sources. Once retrieved, the knowledge facts are incorporated into the answer generation. Success in the VQA setup has led to similar architectures and labeled datasets being adopted in the misinformation detection task. In question answering, we gather evidence to answer a specific question about the input; in fact-checking, we look for evidence that verifies the claims. This verification usually entails the retrieval of related evidence, followed by binary classification or threshold-based similarity checks. In Factify [15], Mocheg[22], CCN [1] we find examples of multimodal fact-checking based on knowledge. While Factify is more of a reasoning task with only one piece of evidence for each modality, Mocheg uses web-scraped image text evidence to verify text-only claims. However, this retrieval is unrestricted, leading to the possibility of retrieving falsified evidence from a propaganda medium, corrupting the final decision.

In [1], we encounter a framework for verifying image-text claims with multiple multi-modal evidence, which are retrieved from news websites. This news website-based retrieval adds credibility to the evidence source. The text and image claim parts are queried to generate cross-image evidence and cross-text evidence. The motivation behind cross-evidence is to check if the image or the text has been used in a similar context. This cross-modality search also means the final retrieved evidence is in the same modality as the claims, ensuring easy uni-modal comparison. The authors propose a memory network-based binary classifier. While the memory network is responsible for the relevant evidence collection, the model is not explicitly designed to point out the clenching evidence (maximally

relevant single evidence) that leads to the decision. [16] addressed this issue with their focus on identifying the relevant evidence first.

2.2 Interpretable models: Structured Representation

While [16] allows for explicitly pointing out which evidence led to the decision, it can not give fine-grained information expressing which parts of the claim are supported by this evidence. This is often a key requirement in Fact-checking, where the reader is interested in knowing how exactly the evidence supports or contests the claim. In [19], the authors propose a supervised multi-label classification scheme trained to add a degree of explainability to their model. The supervised multi-label classifier detects complete changes or swaps in the image or text regions based on its training on a synthetically augmented version of the dataset proposed in [1]. While labels render the model interpretable in terms of the output, it is susceptible to bias due to the synthetic augmentation as well as the final supervision. We argue for structured representation-based reasoning, where we focus on generating representations that can be easily applied to rules and checked for consistency without any learning involved. Such an approach lends itself to be interpretable by design and free from training bias.

2.3 Supervision is Bias

The idea of what is fake and what is not is inherently challenging. In ways, the focus is more about finding and emphasizing differences and not just similarities. The human understanding of what is fake is often a result of complex rationale, prior experience, and the latest evidence. It results in arguments and debates that explain the fairness of a post in terms of support and conflict with external independent evidence and sources. It is more akin to the task of factfinding and applying a set of rules, where the fact-finding is often the bulk of the effort, and the rules are clear and unambiguous. Not unlike legal proceedings or judgments. In the supervised learning setup, this is, however, reduced to a binary label, neglecting all intermediate stages. Treating the problem as a data-driven, learnable task. These methods are, in general, binary classifiers trained with supervision, either from human annotations or from the sampling scheme used to generate them. Such a system has an inherent bias towards the dataset it has been trained on with poor generalization. Even when external knowledge is incorporated into the pipeline to add generalization, the choice of external knowledge is guided by the final supervision.

3 METHOD

Our primary assumption about the claim is that it is presented in the format of a Text-Image pair. Given the claim couplet, we are tasked with verifying the content with evidence. The first part of our work entails retrieving external cross-evidence based on Internet searches. These retrieved evidence are then ranked based on similarity to identify the relevant evidence. Our key insights are 1) fine-grained structured representation of the claim and evidence, which allows us to explicitly point out supports and conflicts while also being interpretable, and 2) supervised learning leads to bias, and thus, a zero-shot approach to detect the said conflicts and

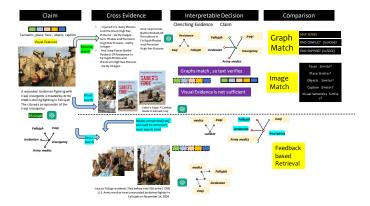


Figure 3: RAV: Entails verifying Claims using Retrieved Evidence. However, instead of end-to-end supervised, trained systems, we propose a zero-shot approach that uses structured representations for both verification and evidence retrieval

supports is more desirable. In Fig. 3 we present our framework, based on the following components.

- Structured Representation of text as Entity Relationship Graphs and images in terms of pretrained visual features
- Comparison Metrics of Entity Relationship Graph (Graph Match) and images (Image Match)
- Multi-modal Feedback based Evidence Retrieval guided by ER graphs
- Interpretable Verification of Claim with Evidence (through Comparison metrics) in terms of Supports and Conflicts

As we can see in Fig. 3, the claim image is represented with a set of visual features while the claim text is converted into an Entity Relationship Graph. The image is used through reverse search to find cross-textual evidence, and the text is used to find cross-visual evidence. The graph-based representation of textual evidence and the visual representation of visual evidence are matched against the original text and image to find supporting and conflicting evidence. The result of the matching is also used to refine the retrieval of cross-evidence. Finally, we can get an interpretable decision in terms of matched nodes, edges and visual features.

3.1 Structured Representation

The image text pairs used in this dataset were originally sourced from news media outlets. Such images are rich in famous personalities and landmarks, in addition to the generic objects. The text, on the other hand, usually discusses named entities. This determines our feature choices detailed below.

3.1.1 Visual Features.

Objects. We use a pretrained detection model[21] to detect N_o object bounding boxes, which are then encoded through a pretrained Mask-RCNN Model[6]. Similar to Cosmos[2], our visual encoding consists of RoIAlign and average pooling to generate visual object embedding $\{\mathbf{v_i^{obj}}\} \in R^{2048}$ (where $i=1,\ldots,N_o$).

Faces. News images are often rich in personality faces, so we use a pretrained face detector [23] to detect N_f faces, which are encoded through the pretrained facing embeddings[18] to generate visual face embedding $\{\mathbf{v}_i^{\text{face}}\}\in R^{512}$ (where $i=1,\ldots,N_f$).

Place. Locations, or scene information is encoded through a pretrained network[24], trained on 365 different types of places, to define our $\{\mathbf{v}^{\mathbf{place}}\}\in R^{2048}$.

Semantic. We use a pretrained network [5] to generate global image semantic features $\{\mathbf{v}^{\mathbf{sem}}\} \in R^{1000}$.

Caption. Finally, we use BLIP[11] to generate an automated caption which we encode through BERT[3], to form $\{\mathbf{v^{cap}}\}\in R^{768}$

Final Visual Features.

$$v = [v_{1,2,...N_0}^{obj}, v_{1,2,...N_f}^{face}, v^{place}, v^{sem}, v^{cap}] \tag{1}$$

- 3.1.2 Text Graph Construction: Build Graph: Given plain text, we want to represent them in a structured way in terms of the named entities and actions/relationships connecting them. Our principal idea is that comparing texts in terms of these graphs leads to a more fine-grained understanding of where the individual texts agree or conflict. We use a large language model to create this ER graph from plain text input. Our cautious use of LLMS is guided by detailed prompts, examples, and checks. We give specific instructions and examples about entity detection and relationship identification focusing on news stories, and we require a particular format that can be easily interpreted as a network graph. This allows us to automatically check graph properties leveraging the networkx library. We combine this with formatting checks and violations of our instructions to reject responses we deem unfit. We define the nodes and edges as:
 - Nodes The detected named entities in the text form the nodes. The named entity nodes are further enriched with facts from an external knowledge base. Similar to [4], we extract a set of candidate knowledge facts for each node and use the tweet text to select the most in-context candidate meaning. Thus, our Node representation consists of details about the type of entity and a contextually relevant description. We encode location and date entities in a specific hierarchical fashion, namely (city, state, country) and (day, date, month, and year), enabling exact correspondence and, thus, easy comparison.
 - Edges The edges connecting two named entities are defined with an explicit extractive action and abstractive description. The action terms are restricted from being directly from the text, whereas their description is generated based on the LLM's knowledge about the action. This abstractive description allows us to map similar actions based on the description, like 'protest' to 'demonstration.'

Evidence Graph: Build Graph Conditional. The texts to be compared are often widely different in their coverage of an event. While the claim may be a 280-character Twitter post, the webscraped evidence text may be a few paragraphs. The graphs natively formed from varying lengths of text can have very different topologies, rendering them hard to compare. We represent an evidence text, focusing on the entities and relationships we have found in the

claim text. We prompt the LLM to focus on the entities in the claim text graph and steer the detection around them. For the relationship we seek to validate, we pass the edges in terms of their participating nodes while masking out the actual action relating to them and its corresponding description and task the LLM to predict them. This implies we force the evidence graph to have an edge between nodes if such nodes are also present in the claim graph and connected by an edge, thereby enforcing a similar graph topology.

3.2 Comparison Metrics

We compare the Claim Text and Image against the retrieved evidence, as shown in Fig 3. Our multi-modal verification involves checking for 1) **Image match** by comparing the claim Image and the cross Evidence Image (XV) and 2) **Graph Match** by checking the claim text against the Cross Evidence Text (XT).

- 3.2.1 Visual Metric: **Image Match**. For visual verification, we score the semantic, place, face, and object and automated caption features of the claim and retrieve evidence in terms of the cosine distance of their embeddings. If any three of the 5 scores are similar beyond Image similarity threshold of 0.9, we consider the images as matched.
- 3.2.2 Text Metrics: **Graph Match**. For the text verification, we compare the ER graphs from the Claim and Evidence text. Our assumption is that for a True Claim, every edge in the Claim graph must have a corresponding edge or walk in the Evidence graph. We achieve this through
 - Entity Matching: Map Nodes to check if similar nodes exist in the Evidence graph
 - Conflicts in Nodes: Find Conflict to check if the said mapped nodes have any conflict in terms of location and date
 - and finally Edges Matching: Find Support to check if claim edges are connected by a semantically similar edge or walk in the evidence text.

Entity Matching. Same entities may be represented slightly differently across texts, and thus, instead of an exact name-matching-based correspondence, we take into account the node details specific to the entity. Our prompting scheme enforces such details in an entity type-specific predefined format. Thus, the nodes are encoded in terms of their name and description using pretrained word embeddings. We solve the node correspondence as a linear assignment problem through a modified Hungarian algorithm. The cosine distance between the node embeddings is used to define the cost matrix for the Hungarian. For a given node, we mask its cost related to the nodes of the same graph, forcing it to be mapped to nodes of the other graph.

Check for Conflicts in the nodes in terms of Location and Date. While news articles may talk about similar people and events, their contextual details in terms of location and date distinguish them. Thus, in this step, we check if the nodes mapped in the previous stage are consistent in terms of the location and date type entities in their neighborhood. The hierarchical nature of formatting allows for the dealing of missing values in terms of city or state name or month. We deem a pair of matched nodes consistent in terms of

location when they share the same location type entity in their neighborhood. A conflict is raised when the nodes have different location-type entities. A similar logic is applied to check for date checks. Any inconsistency in this stage leads to rejection of the mapping.

Edge Matching to find Supported Claim edges . For a given edge (a,b, action) in the claim graph, we check if the corresponding nodes a' and b' in the evidence graph, found using Hungarian in the previous stage, are connected in the evidence graph by a walk. However, the presence of a walk is not enough, as this walk could be contesting (disagreeing with) or verifying (agreeing with) the claim. Thus, we check the semantic similarity of this walk on the evidence graph against the claim edge. We collate the action terms along the walk and compare the cosine similarity against the claim action in terms of BERT embeddings [3]. Thus, edges can be marked as 'unconnected' if the nodes are not connected in the evidence graph. Otherwise, they can be marked 'verified' based on semantic similarities. This fine-grained marking of edges allows us to explicitly point out which parts of the claim were verified. This edge-matching scheme allows us to combine multiple evidence graphs and reason about the status of the claim edges simultaneously.

We output this fraction of claim edges verified as the measure of overall support for this claim given the evidence.

3.3 Evidence Retrieval

Given an Image-Text Claim, we define Text Cross Evidence as the text evidence obtained by reverse search with the Image Claim, and similarly, Visual Cross Evidence as the visual evidence obtained by direct search with the Text Claim. In Fig. 3, we show an example of a text-image claim and the retrieved evidence and cross-evidence. For the NewsClIPpings dataset, we use the retrieved Cross evidence provided [1] as part of the dataset. For Remiss, we collect evidence following the scheme below:

3.3.1 **Text Cross Evidence : Reverse Search**. We use **Google Reverse Search** on the claim image to find Text Cross Evidence. This Text allows us to find the context in which the claim image has been used in. However, this reverse search works best for content that is already widely published and is not as effective when tested on user-posted images on social media.

3.3.2 Visual Cross Evidence: Direct Search. We query the Google powered Programmable search engine with the text claim to collect Visual Cross Evidences. When the text claim is brief and factual, it can be used in this manner to query the Internet to find close matches, as can be seen with our experiments in AP1. For more verbose text claims, we often need to summarize the text and create specific search terms. However, the specific search terms that might work for an image depend on the annotation the source website provides. Thus, we adopt a feedback-based image retrieval, where we use LLM and measure similarities with the claim image to guide the search term generation.

Feedback based Retrieval. For NewsCLIPpings images, text pairs are sourced from news websites. The texts remain intact in

the dataset. Thus, a direct search with the text returns the corresponding news item, image, and text exactly the same from the news websites in most cases. However, evidence retrieval using internet searches becomes non-trivial when the text in the claim is even slightly rephrased, or in the case of the tweet data, where the users express their opinion on a news event in their own words.

We propose a feedback-based retrieval scheme that leverages our structured representation of the query text to guide the search. We use pretrained visual networks, detailed in 3.1.1, to score the similarities between the claim and retrieved evidence images that form our visual feedback. This is combined with text feedback comprising of the graph comparison results of the claim text and the text scarped along with the retrieved image. This visual and text feedback is used to propose a modified search term. In particular, we get visual similarity scores for objects, semantic, place, face, and caption, which is communicated to the Large Language model to modify the search string in terms of the named entities corresponding to semantics, place, and person from the graph.

3.4 Interpretable Verification with Graph Match and Image Match

We interpret a News story as a collection of named entities that exist in the real world and a set of relationships or associations claimed by the news story. While in the past, people have tried to judge stories in their entirety as Fake or Pristine, we focus on trying to find out which parts of the story are true because we have evidence for it in the external world and which parts of the news can not be verified or are contested. Given an image text multi-modal post, our idea is to use the retrieved multi-modal evidence and independently verify the textual and visual aspects of the claim.

For the **visual verification**, we look for exact matches from among the retrieved evidence. So, we measure the images in terms of their pretrained feature similarity but only accept matches beyond high thresholds. As discussed in the previous section, our **Image Match** scheme checks for visual aspects that are specific to news items encoding the images in terms of semantics, places, objects, faces, and automated caption. This allows us to explicitly point out how the evidence image matches or contests the claim image.

We measure the **Truthfulness of a text claim**, represented as an ER graph, in terms of **Supported Claim Edges** and **Conflicts in Nodes** courtesy of our **Graph Match** scheme. This, of course, depends on the complexity and verbosity of the claim and the available evidence. In Fig 11, we compare our accuracy against the number of claim edges in the sample. It demonstrates that claims are that the either very generic (having 2 or less edges) or very verbose (more than 4 edges) are where we struggle. For the majority of the samples the number of claims were around 3, for which our performance is comparable with the state-of-the-art. Finally we highlight against that our False Negatives are always lower than our False Positives, because as part of our design choice we wanted to prioritize detection of fakes over verification of Pristine samples.

4 DATASETS

We present our results on synthetic and a real-world sample set, NewsCLIPpings [13], and REMISS.

Table 1: Dataset Comparison : NewsCLIPpings(synthetic) vs Remiss(real)

	NewsCLIPpings(Test)	Remiss		
	Image-caption pairs from	Tweets Collected		
Source	The Guardian, BBC, USA	During Elections		
	Today, Washington Post	in Barcelona in 2019		
labels	Fakes or OOC generated	Manual Annotation		
labels	by swapping captions	Manual Annotation		
samples	7233	100		
Text Evidence	Reverse search (fails 2033)	Reverse search (fails 83)		
Visual Evidence	Direct Search with	Human with		
visual Evidence	Claim Text	Feedback Retrieval		

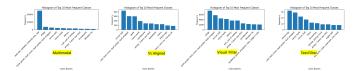


Figure 4: Remiss: Top 10 Image Classes, across filter stages



Figure 5: Samples rejected for verification: Because of Lack of VL alignment and Political Content

4.1 REMISS Dataset

The dataset originates from 300943 tweets collected from Spanish users during elections in Barcelona in 2019. In the following section we discuss our filtering stages which consist of

- Multi modal
- Visual Language Alignment
- Visual Filter
- Text Filter

In Fig. 4 we the histogram of the top 10 classes as we undertake our filtration schemes. In Fig. 5 we show examples of multimodal samples rejected, while Fig. 7 shows the samples we filter for verification.

4.1.1 Multi Modal Samples. 241827 of the 300943 or Around 80% of the tweets were accompanied by an image. When we discount reposts we find a total of 168651 Image-text pairs which are probable candidates for verification.

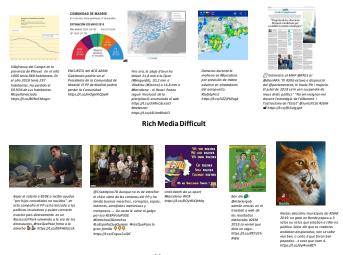


Figure 6: Visual Filter of Rich Media Content and Memes

4.1.2 Visual Language Alignment. Our premise of using cross evidence to fact check multimodal post is based on the image and text (in the post) are aligned, and are expressing some shared idea. The less abstract and more explicit this shared concepts are, the easier it is to question them. Symbolism, in text or visual, renders multimodal comparisons opaque and evidence retrievals hard. For example, symbolic visuals are not just hard to compare with the text, they are also hard to find evidence for when we are use the text as query. If tweet about a protest is accompanied by an symbolic image of protest, it is hard to verify or refute, On the other hand when the tweet is accompanied by a real image of a protest, by finding this image and checking what the source one can support or refute the tweet text claim, Our method works at its best when the images are not for symbolic purposes and are expressing important details the tweet mentions, that are semantically aligned. In this work we compare automatically generated BLIP caption similarity with text claim to filter out weakly aligned text image pairs.

4.1.3 Visual Filter: Reject Rich Media web content. As we can see in Fig.4 there is strong bias for image content that is of type 'website', this refers to rich media images or charts, diagrams what are from news website often in the form of screen shots. In Fig. 6 we show examples of such samples in the top row. These text heavy images with poor quality visual content are difficult to compare or find in the internet. We use the image net class labels to reject rich media images from news papers or websites. In Fig. 6 bottom row we see examples of memes, that are trivially classified as fake due to lack of supporing evidence, as show in Fig. 8

4.1.4 Text Filter: Select Political Content. While this subset of aligned text and image pairs make good candidates for verification of generic content in social media, This particular dataset was collected during election period aided by Journalists, and thus to leverage the dataset we focus on content that is political in nature The team of journalists had historical fake news data about users and contents which was used to train a decision tree based binary

Table 2: Remiss Filter:

Total	Tweet Text	300943
Multimodal	Tweet Text has an Image	168651
Visual Text Aligned	cosine similarity (Blip(image),text) > 0.40	15490
Visual Filter	Image not of type 'website,internet'	11090
Text Filter	Fakeness Score > 0.45	420
with Evidence	Collected through Feedback Retrieval	100



Figure 7: Samples Accepted for verification

classifier to detect suspicious text a cite. This acts as our filter to seek suspicious posts that may require verification.

4.1.5 Evidence retrieval. Evidence retrieval was a challenge, and in the end, we used a human-in-the-loop approach to annotate 100 samples. The collection consist of an equal number of Fake and Pristine samples Our feedback retrieval is particularly useful when it comes to finding images for texts stories that have been subjectively retold, and thus benefits from an objective structured representation.

News Sources. elpais.com, elmundo.es, abc.es, lavanguardia.com, larazon.es, naciodigital.cat, marca.com, granadahoy.com, ecuadoretxea.org, eldiario.es, diariocordoba.com, publico.es, beteve.cat, radiosabadell.com, elespanol.com

In Fig. 8 we demonstrate our evidence retrieval across different types of multimodal posts. In row 1, we see that memes are trivally marked as fake, because of lack of supporting evidence. For rich media in row 2, we see that despite retrieving relevant evidence, the visual nature of graphs, charts makes it hard to compare with the collected evidence, thus these are posts our method fails to deal with. Row 3 shows examples of art, street art in this case, which is often hard to find evidence for without artist information. Finally in row 4, 5 we show that protests and public events are well covered in News Media, leading to correct evidence retrieval and verification.

5 EXPERIMENTS AND ANALYSIS

5.1 Results: Disinformation Detection

Our results on the binary task of Disinformation Detection are presented in Tab. 3.

Related Methods and Baselines.

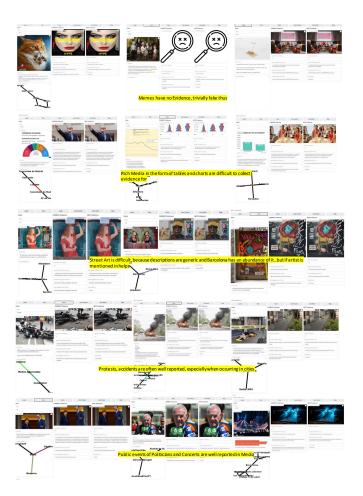


Figure 8: Evidence Retrieval: Accross Post Types

- CLIP [13] does not use any evidence but passes image and text through separate encoders to learn a binary Classification task.
- CCN [1] proposes the use of Cross Evidences to learn a binary Classification task.
- RED [16] highlights the need to point to relevant evidence.
 They create a dataset of relevant irrelevant evidence based on cosine similarity with the claim and train a binary classification task of fake or not that leverages this idea of relevance. As noted earlier, this allows them to point to the evidence that led to the decision, but they can not process the evidence in a fine-grained manner to say which parts of the evidence led to the decision.
- Baseline TS is our similarity-based baseline, where we find thresholds from the validation set. For the visual elements, the similarity is similar to RAV, where we consider the cosine distance of pretrained features about semantics, place, and objects. For text, we use cosine distance between Bert embeddings.
- Baseline VTA is our baseline based on a supervised transformerbased setup. It is similar to the CCN Method in terms of

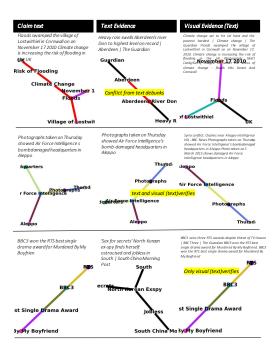


Figure 9: We show examples of Entity Relationship graphs in terms of claim, text, and text from visual evidence. Matched nodes and edges (or walks) share color. Nodes that are conflicted in terms of Location or Date data in their neighborhood are marked red. The conflicted edges are also marked red. In the 1st example, Floods and Aberdeen conflict because of locations 'Village of Lostwithiel' and 'Aberdeen.' In the 2nd example, we see both the evidence validate the claim. In The 3rd example, we see there are no conflicts. The text evidence does not share any entities or relationships, but there is no conflict in terms of the detected place or location. The only verification comes from the text of the visual evidence, which is only helpful when the visual evidence matches the claim.

the features used, but instead of using a memory network to capture relevant evidence, it uses an end-to-end transformer framework trained on the final label.

Our results validate that RAV is comparable with state-of-the-art methods while maintaining high accuracy in rejecting fakes despite the zero-shot setting. The inclusion of evidence leads to better results, as can be inferred from the improvements due to CCN over CLIP, validating the idea that fact-checking should be evidence-based. But in general, the supervised evidence-based fact-checking models proposed perform similarly on the task of detecting fakes versus pristine; our baseline VTA model performs comparable to the State of the art but often deems news Pristine even without credible evidence or any evidence at all. The learning, however, does not transfer well to the Spanish Fake News, which can be attributed to the quality and style of remiss data discussed in Sec. 5.3.

Table 3: OOC Detection: Baselines vs. RAV: Our Primary observation is our competitive results without any *sup*ervision. While our system fails to verify some real news, it does better than others in rejecting fake news. *knw* refers to knowledge or evidence and *sup* refers to supervision. 'T' means 'True,'

	Method	Knw	Sup	NewsCLIPpings			Remiss		
				Accuracy			Accuracy		
				Overall	Fake	Pristine	Overall	Fake	Pristine
1	CLIP[13]	-	T	66.1	56.4	75.7			
2	CCN[1]	T	T	84.7	84.8	84.5	-	-	-
3	RED[16]	T	T	87.9			-		
4	VTA	T	T	87.4	86.4	88.4	44	42	46
5	TS	T	-	74.5	82.3	66.5	52	78	26
6	RAV	T	-	87.2	91.1	83.4	65	82	48

5.2 Structured Representation

Text Graph Comparision is better than Global Similarity. We believe that detecting fakes is more important than verifying pristine. This can be easily achieved with high similarity thresholds, as we can see in our baseline TS. Our improvements over baseline TS highlight the discriminative nature of our ER graph representation over global word embeddings as both the methods use the same visual channel; as we see in our results in Fig.9 representing the text as Entity Relationship enables us to highlight details relevant to our task. The first example shows that both the text and the Text evidence are about Floods in the UK; structured Representation quickly points out the conflict in terms of the location type 'Aberdeen' and 'Village of Lostwithiel.' This also allows us to set high thresholds for node similarity and avoid false positives, as now we will only match entities against other instances of the same entity type; but in this specific case, they are both from the UK, which might mean their semantic embeddings are similar. For locations and Dates though we use a hierarchical representation and exact matching as discussed in Sec.3.1.2, and thus in this example, 'Village of Lostwithiel' is actually represented in the graph as $ent_{type}: LOCATION, data: Lost with iel, Cornwall, UK and 'Ab$ erdeen' as ent_{tupe} : LOCATION, data: Aberdeen, unk, Scotland. For Remiss, the texts are very different, and global semantics don't work so well. Our high thresholds mean we reject most evidence when applying baseline TS, and it is only when we introduce finegrained structured representation through RAV that we are able to identify supports and conflicts.

Conditioning on claim helps retain structure. In Fig. 10 we see how texts which vary widely in sentence structure and content result in structurally dissimilar graphs, which are often hard to compare, as seen in row 1. As discussed in Sec. 3.1.2, Conditional Graph is essential for Comparing texts of Varying length, by focusing the graph construction on entities and relationships present in the claim.

5.3 Qualitative Results: Real Vs lab

5.3.1 Quality of Claims.

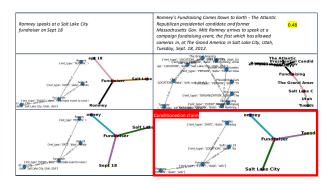


Figure 10: Conditional Graph helps preserve structure. In the top row we compare two texts in terms of their generated graphs, note despite the texts not being similar, only 0.48 score, yet we can detect the common nodes and edges, colored similarly in the annotated simplified graph shown to the right of the actual graph. In the bottom row we see how conditioning the entity and relation detection on the claim allows us generated a similarly structured graphs, which leads to detection of more nodes and edges

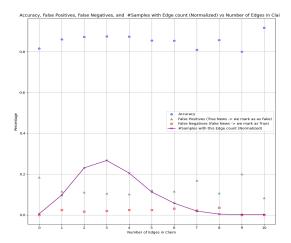


Figure 11: We plot the accuracy against the number of claims in the input text for the NewsCLIPpings dataset. Samples per edge count is the fraction of input samples with a particular edge count. We can see most claims consist of 2 to 4 edges.

Text. For NewsCLIPpings, the claim texts are sourced from News websites, thus maintaining a particular journalistic format characterized by objectivity, relevant details, and brevity; in Remiss, the retelling of the text happens subjectively and often with a strong bias. This verbosity affects both the formation of the ER graphs and the retrieval of evidence.

Image. The NewsCLIPpings images are mostly professionally taken pictures already published on news websites. For Remiss, the images are mostly taken by individuals and often differ in visual perspective from the ones reported by journalists on news websites, as seen in Fig. 15 row 2 and Fig.14 row 1. While these

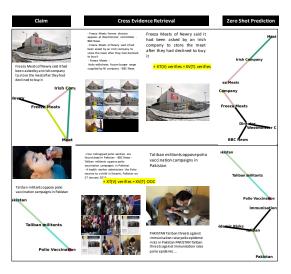


Figure 12: We show examples of Verification in NewsCLIPpings dataset

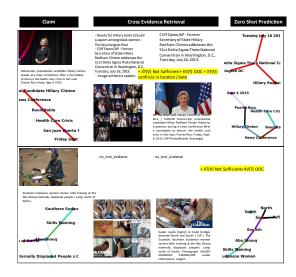


Figure 13: We show examples of Fake Detection in NewsCLIPpings dataset

are both pristine samples and the visual evidence retrieved are also correct, is only the widely varying perspective between the claim and evidence in Fig.14 that lead to OOC decision.

5.3.2 Retrieval.

Direct Search. In Direct search, we use the claim text. Because of the publisher origin of NewsCLIPpings, the style of the text also acts as a clue and often returns exact matches, as seen in Fig. 12, row 1. For Remiss, we never encounter exact text matches from direct search, and spend the bulk of our effort in the retrieval stage, with a Human in the loop feedback-based retrieval resulting in exact matches, eg, Fig.15. Even for the returned search results, which are mostly from Google's cache, the link cannot often be traced back

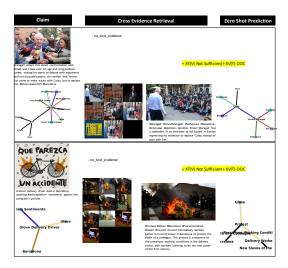


Figure 14: We show examples of Failures in Remiss dataset

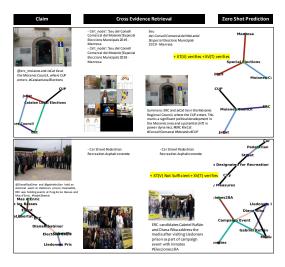


Figure 15: We show examples of Verification in Remiss dataset

to its source for contextual text. While we did encounter cases of pages being updated leading to this, the major reason was actually paywalls. Finally, retrieval is also limited by its actual coverage on the news websites.

Reverse Search. For NewsCLIPpings, the reverse search with image claim returns results for around seventy percent of cases. This is despite the already published nature of the source images. For Remiss, reverse search with an image rarely returns results apart from automatically detected entities. We hypothesize that the absence of published exact forms in mainstream media is one of the causes.

5.3.3 Evidence.



Figure 16: Feed Back Based Retrieval: Use unmatched nodes to construct text search term

Visual. Visual similarity, from a verification perspective, is a challenge on its own. In this work, we use visual similarity to reduce our search space and mostly rely on contextual text extracted from sources for support or conflict. This means we even find images from alternate visual perspectives ranked higher because of the contextual text. For Remiss, such contextual text varies widely from the claim in terms of style and length. Our image similarity measure is also useful for identifying exact matches, particularly valuable in scenarios where contextual text is absent. Such exact matches are often found in NewsCLIPpings.

Text. Text Evidence, when available from exact matches, is telling. In NewsCLIPpings, we see text evidence that is useful for detecting conflicts with claim text. For Remiss, text evidence is rare, and we mostly rely on visual evidence for support.

5.4 Feed Back Based Retrieval

Our feedback retrieval is particularly useful when it comes to finding images for texts stories that have been subjectively retold, and thus benefits from an objective structured representation. In Fig. 16 we see its application to the real world remiss dataset, where we often have to go to multiple search term refinement to find the correct image.

Sources for Remiss are Spanish News Sites including. elpais.com, elmundo.es, abc.es, lavanguardia.com, larazon.es, naciodigital.cat, marca.com, granadahoy.com, ecuadoretxea.org, eldiario.es, diariocordoba.com, publico.es, beteve.cat, radiosabadell.com, elespanol.com

5.5 Fail Cases

In Fig. 17 we show how we reject samples as fake, if the visual content is symbolic, as this visual claim can not be meaningfully compared with the visual evidence from the text. In Fig. 18 we show how often even with poor evidence the trained VTA Model makes predictions which are correct. Our RAV based model rejects all these as fakes, due to the lack of evidence.

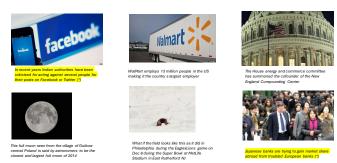


Figure 17: Fail Cases: We Mark pristine samples as fake, because the visual claims are symbolic, note how the VTA baseline often marks these as pristine, marked with yellow

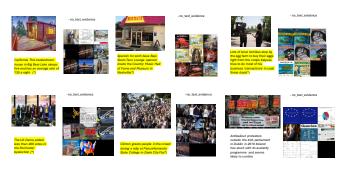


Figure 18: Fail Cases: We Mark pristine samples as fake, because the visual claims are could be not found, note how the VTA baseline often marks these as pristine, marked with yellow

5.6 Parameters and Thresholds

- Node Similarity Threshold is used to reject mapping during Node Matching using Hungarian. We set this value to 0.8, making sure only nodes that match beyond this threshold with their name and description field in terms of Bert Similarity.
- Edge Similarity Threshold is used to reject connected edges or walks in the evidence graph during Edge Matching. We set this value to 0.5, making sure only edges or walks that match beyond this threshold with their action field in terms of Bert Similarity. Edge threshold is only applied to connected edges or walks.
- Image Similarity Threshold is set to 0.9 for all types of image features (face, place, object, caption). If any 3 of these pass the threshold, we consider the image matched visually.
- Edge Support Threshold is the minimum fraction of supported edges for Graph match; this is set to 0.3.
- Graph Conflict Threshold is set to the number of conflicts we tolerate. We don't tolerate any conflict, and this threshold is set at zero.

5.7 Use of Large Language Model (LLM)

We are careful not to use LLMs to make any decision. Our use of LLMs is restricted to generating ER graphs and Search terms. We also don't use LLM to build any dataset or synthetic data to train models. We leverage the NLP abilities of LLM to detect entities and relationships. While we have experimented with Mistral, Orca, and llava, we found Chatgpt from Openai to be the most useful in terms of the quality of the generated ER graphs and following our instructions regarding graph structure and output format. We use gpt-3.5turbo for all our LLM tasks.

6 CONCLUSION

Tackling misinformation is a technically challenging problem, but it has huge ramifications in this new world of post-truth. In this work, we looked at the specific case when real images are taken out of context and insidiously used to spread propaganda. We show that with the use of structured representation and rule-based matching, one can place news in context and thereby explain which parts are supported and which are conflicted.

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