Abstract

Even to a simple and short news headline, readers react in a multitude of ways: cognitively (e.g., inferring the writer’s intent), emotionally (e.g., feeling distrust), and behaviorally (e.g., sharing the news with their friends). Such reactions are instantaneous and yet complex, as they rely on factors that go beyond interpreting the factual content of the news headline. Instead, understanding reactions requires pragmatic understanding of the news headline, including broader background knowledge about contentious news topics as well as commonsense reasoning about people’s intents and emotional reactions.

We propose Misinfo Reaction Frames, a pragmatic formalism for modeling how readers might react to a news headline cognitively, emotionally, and behaviorally. We also introduce a Misinfo Reaction Frames corpus, a dataset of over 200k news headline/annotated dimension pairs with crowdsourced reactions focusing on global crises: the Covid-19 pandemic, climate change, and cancer.

Empirical results confirm that it is indeed possible to learn the prominent patterns of readers’ reactions to news headlines. We also find a potentially positive use case of our model; when we present our model generated inferences to people, we find that the machine inferences can increase readers’ trust in real news while decreasing their trust in misinformation. Our work demonstrates the feasibility and the importance of pragmatic inferences of news to help enhance AI-guided misinformation detection and mitigation.

1 Introduction

Effectively predicting how a headline may influence a reader requires knowledge of how readers perceive the intent behind real and fake news. While most prior NLP research on misinformation has focused on fact-checking, preventing spread of misinformation goes beyond determining veracity (Schuster et al., 2020; Ren et al., 2021). For example, in Figure 1, government mistrust fears may lead readers to share pandemic conspiracy headlines like “Epidemics and cases of disease in the 21st century are "staged"” despite correctly predicting it is misinformation. The widespread circulation of misinformation can have serious negative repercussions on readers — it can reinforce sociopolitical divisions like anti-Asian hate (Vigen et al., 2020; Abilov et al., 2021), worsen public
<table>
<thead>
<tr>
<th>News Headline</th>
<th>Writer’s Intent</th>
<th>Reader Reaction</th>
<th>Spread</th>
<th>Real News? (GPT-2 / T5 / Gold)</th>
</tr>
</thead>
<tbody>
<tr>
<td>How COVID is Affecting U.S. Food Supply Chain</td>
<td>Human: “the pandemic is interrupting the flow of groceries to consumers”</td>
<td>Human: “want to know how their groceries will get to them”</td>
<td>4.0</td>
<td>✓ / ✓ / ✓</td>
</tr>
<tr>
<td></td>
<td>GPT-2: “food supplies are being affected by covid”</td>
<td>GPT-2: “want to learn more”</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>TS: “food supply chain is affected by covid”</td>
<td>TS: “want to find out more information”</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Thai police arrested a cat for disobeying the curfew order.</td>
<td>Human: “governments are ludicrous and obtuse.”</td>
<td>Human: “feel disbelief”</td>
<td>1.0</td>
<td>X / X / X</td>
</tr>
<tr>
<td></td>
<td>GPT-2: “animals can be dangerous”</td>
<td>GPT-2: “feel worried”</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>TS: “lockdowns are enforced in thailand”</td>
<td>T5: “feel shocked”</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Perspective — I’m a black climate expert. Racism derails our efforts to save the planet.</td>
<td>Human: “since climate change will likely affect poorer nations, rich societies are not motivated to help”</td>
<td>Human: “want to improve their own behavior towards others”</td>
<td>3.0</td>
<td>✓ / X / ✓</td>
</tr>
<tr>
<td></td>
<td>GPT-2: “racism is bad”</td>
<td>GPT-2: “want to learn more”</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>T5: “racism is a problem in society”</td>
<td>T5: “want to take action”</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 1: Example instances in MRF corpus along with generations from reaction inference models fine-tuned on the corpus. We show the predicted writer intent (human and machine-generated), reader reactions (either a perception or action) and gold label, as well as the human-annotated likelihood of the headline being shared. Our task introduces a new challenge of understanding how news impacts readers. As shown by the examples, large-scale pretrained models like GPT-2 large and T5-large miss nuances present in perceptions of informed readers even when they predict the correct label.

health risks (Ghenai and Mejova, 2018), and undermine efforts to educate the public about global crises (Ding et al., 2011).

We introduce Misinfo Reaction Frames (MRF), a pragmatic formalism inspired by Frame semantics (Fillmore, 1976), to reason about and predict the effect of news headlines on readers. Similarly to semantic frames, our pragmatic frames allow us to consider contextual information when determining meaning. However, our pragmatic frames capture richer meaning relating to writer intents and reader reactions than semantic frames. Such implications, which rely on situational commonsense reasoning and cognitive psychology, would be difficult to model in a purely categorical schema.

We use our new formalism to collect the MRF corpus, a dataset of 202.3k news headline/annotated dimension pairs (69.8k unique implications for 25.1k news headlines) from Covid, climate and cancer news. These annotations convey six dimensions of how news headlines provoke reactions from readers - (1) perceived writer intentions (e.g. “to imply 5G causes Covid”), (2) emotional reactions (e.g. “feeling scared”), (3) behavioral reactions (e.g. “wanting to go to a climate protest”), (4) likelihood of sharing a news headline, (5) the perceived reliability, and (6) the actual reliability assessed by fact-checking experts (gold label). For example, given the headline “Thai police arrested a cat for disobeying the curfew order,” in Table 1, our frame captures the emotional reaction that a reader might feel “disbelief”.

We train reaction inference models to predict MRF dimensions from headlines. As shown by Table 1, reaction inference models can correctly label news (our best model achieves 85% F1) and infer commonsense knowledge like “a cat arrested for disobeying curfew implies lockdowns are enforced”, but are challenged by more nuanced implications “a cat arrested for disobeying curfew is nonsensical and therefore implies government incompetence.” We propose reaction frame inference as a natural language generation problem to allow generalization to emerging social behaviors and trends in misinformation. Notably, we can achieve 86% F1 on a new cancer domain by finetuning our MRF model on 574 annotated examples.

To showcase the usefulness of this paradigm, we investigate the effect of MRF explanations on
reader trust in headlines with a user study. Notably, our results show that machine-generated MRF inferences affect readers’ trust in headlines and for the best model there is a statistically significant correlation (Pearson’s $r=0.24$, $p=0.018$) with labels of trustworthiness ($\S$7.3).

Our framework and corpus highlight the importance of understanding the implications of news headlines with respect to reader reactions. We will publicly release the MRF corpus and trained models to enable further work on combating the spread of misinformation. The full data annotation setup can be found here: https://misinfo-belief.github.io/, for use in extending reaction frames to other news domains.

## 2 Misinfo Reaction Frames

Table 1 shows real and misinformation news examples from our dataset with headlines obtained from sources described in $\S$3. We pair these headline examples with generated reaction frame annotations from the MRF corpus. Each reaction frame contains the following elements:

### Headline
We elicit annotations based on a news headline, which summarizes the main message of an article. We explain this further in $\S$3. An example headline is “Covid-19 may strike more cats than believed.”

### Writer Intent
A writer intent implication captures the readers’ interpretation of what a headline means. For example, given the headline “An “official” mask to combat the novel coronavirus was released,” a reader might infer that the writer implied that “some masks are better than others.” This will be influenced by a reader’s belief system, as readers may infer more benign intents from headlines with implications that reinforce prior beliefs. To provide structure, we define these implications as relating to one of 7 common themes (e.g. technology or government entities) appearing in Covid and climate news.

### Reader Perception
A reader perception implication describes how readers would feel in response to a headline. These inferences include emotional reactions (e.g. “feeling angry”) and observations (e.g. “feeling that the event described in the headline would trouble most people”).

### Reader Action
A reader action implication captures what readers would do in response to a headline. These implications describe actions a reader would want to take after reading about the news event described in the headline (e.g. “wanting to protect their cats”).

### Likelihood of Spread
To take into account variability in impact of misinformation due to low or high appeal to readers, we measure the likelihood of an article being shared. For this, we score the headline based on how likely it is that readers would share the article given the headline. We use a 1-5 Likert scale (Likert, 1932) with the following categories: {Very Likely, Likely, Neutral, Unlikely, Very Unlikely}.

### Perceived Label
We elicit the perceived label (real/misinfo) of a headline, i.e. whether it appears to be misinformation or real news to readers. This provides information about which headlines are more or less likely to confuse readers.

### Gold Label
We include the original ground-truth headline label (real/misinfo) that was verified by fact-checkers. This allows us to compare performance of misinformation detection systems trained on the MRF corpus.

<table>
<thead>
<tr>
<th>Theme</th>
<th>Climate</th>
<th>Covid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Climate Statistics</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Natural Disasters</td>
<td></td>
<td>✓</td>
</tr>
<tr>
<td>Entertainment</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Ideology</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Disease Transmission</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Disease Statistics</td>
<td></td>
<td>✓</td>
</tr>
<tr>
<td>Health Treatments</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Protective Gear</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Government Entities</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Society</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Technology</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

Table 2: Themes present in articles by each news topic. Some themes (e.g. society, technology) are covered by both climate and Covid domains, while others are domain specific.

## 3 News Data Collection

We examine reliable and unreliable headline extracted from two domains with widespread misinformation: Covid-19 (Hossain et al., 2020) and climate change (Lett, 2017). We additionally test...
on cancer news (Cui et al., 2020) to measure out-of-domain performance.

3.1 Climate Change Dataset

We retrieve both trustworthy and misinformation headlines related to climate change from NELA-GT-2018-2020 (Gruppi et al., 2020; Norregaard et al., 2019), a dataset of news articles from 519 sources. Each source in this dataset is labeled with a 3-way trustworthy score (reliable / sometimes reliable / unreliable). We discard articles from “sometimes reliable” sources since the most appropriate label under a binary labeling scheme is unclear. To identify headlines related to climate change, we use keyword filtering. We also use claims from the SciDCC dataset (Mishra and Mittal, 2021), which consists of 11k real news articles from ScienceDaily, and Climate-FEVER (Diggelmann et al., 2020), which consists of more than 1,500 true and false climate claims from Wikipedia. We extract claims with either supported or refuted labels in the original dataset.5

3.2 Covid-19 Dataset

For trustworthy news regarding Covid-19, we use the CoAID dataset (Cui and Lee, 2020) and a Covid-19 related subset of NELA-GT-2020 (Gruppi et al., 2020). CoAID contains 3,565 news headlines from reliable sources. These headlines contain Covid-19 specific keywords and are scraped from nine trustworthy outlets (e.g. the World Health Organization).

For unreliable news (misinformation), we use The CoronaVirusFacts/DatosCoronaVirus Alliance Database, a dataset of over 10,000 mostly false claims related to Covid-19 and the ESOC Covid-19 Misinformation Dataset, which consists of over 200 additional URLs for (mis/dis)information examples.5 These claims originate from social media posts, manipulated media, and news articles, that have been manually reviewed and summarized by fact-checkers.

3.3 Cancer Dataset

We construct an evaluation set for testing out-of-domain performance using cancer real and misinformation headlines from the DETERRENT dataset (Cui et al., 2020), consisting of 4.6k real news and 1.4k fake news articles.

4 MRF Corpus Annotation

We obtain 69,885 news implications (See §3) by eliciting annotations for 25,164 news headlines (11,757 Covid related articles, 12,733 climate headlines and 674 cancer headlines). In this section we outline the structured annotation interface used to collect the dataset. Statistics for the full dataset are provided in Table 3.

4.1 Annotation Task Interface

Misinfo Reaction Frames are annotated using the Amazon Mechanical Turk (MTurk) crowdsourcing platform. The layout of our annotation task is given in Figure 2. For ease of readability during annotation, we present a headline summarizing the article to annotators, rather than the full text of the article. We structure the annotation framework around the themes described in §2.

4.2 Quality Control

We use a three-stage annotation process for ensuring quality control. In the initial pilot, we select a pool of pre-qualified workers by restricting to workers located in the US who have had at least 99% of
their hits approved and have had at least 5000 hits approved. We approved workers who consistently submitted high-quality annotations for the second stage of our data annotation, in which we assessed the ability of workers to discern between misinformation and real news. We removed workers whose accuracy at predicting the label (real/misinfo) of news headlines fell below 70%. Our final pool consists of 80 workers\(^9\) who submitted at least three annotations during the pilot tasks. We achieve pairwise agreement of 79% on the label predicted by annotators during stage 3, which is comparable to prior work on Covid misinformation (Hossain et al., 2020). To account for chance agreement, we also measure Cohen’s Kappa $\kappa = .51$, which is considered “moderate” agreement. Additional quality control measures were taken as part of our extensive annotation post-processing. For details, see Appendix A.3.

5 Analysis of Reaction Frame Annotations

We conduct a series of analyses using gold inferences in the MRF corpus to better understand how readers perceive and act upon misinformation compared to real news.

\(^9\)See Appendix A.1 for annotator statistics.

Effect of Reader Perception on Article Sharing

Annotators tended to be cautious in reported sharing behavior. We found that annotators did have a higher likelihood of sharing real articles over misinformation articles (Table 5), and importantly generally claimed that they would not share articles that they thought were misinformation. For 1.2% of articles reported as misinformation in the training set annotators did provide a likelihood of sharing $\geq 4$. We show examples of articles that were labeled as “misinfo” but shared anyway in Table 4. While the reasoning for this is unclear, the annotators’ reaction frame predictions for reader perceptions and actions may provide insight. For example, annotators were skeptical of the misinformation news event “Coronavirus was created in Wuhan lab and released intentionally.” but said they would share it anyway and provided “readers would feel curious” and “readers would want to know if the wild claim has any truth to it” as related inferences. Concerningly, this indicates even very obvious misinformation may still be shared by generally knowledgeable readers when it contains content they deem particularly interesting or they want to corroborate the article content with others. Overall, however, we found that annotators’ perception of an article as being more reliable played a positive role in their decision to share it.

6 Modeling Reaction Frames

We test the ability of large-scale language models to generate inferences for unseen news headlines using conditional generation (Sutskever et al., 2014; Rush et al., 2015). We use topic- and dimension-based special tokens to control generation of reaction frames for T5 encoder-decoder (Raffel et al., 2020) and GPT-2 decoder-only models (Radford et al., 2019). Both models are based on a transformer architecture (Vaswani et al., 2017). For predicting the gold label, we use either the generative models or BERT-based discriminative transformer models (Devlin et al., 2019).

6.1 Training

Given a headline $h$ of length $T$ tokens, topic token $s_t \in \{[covid],[climate]\}$ and dim token $s_d$ representing one of six reaction frame dimensions, we pass the following input vector $x$ to our generative language model:

$$x = h_1 \ldots h_T \parallel s_d \parallel s_t.$$
News Event (Spread)

| Why Companies Are Making Billions of COVID-19 Vaccine Doses That May Not Work (4.0) | Pred/Gold |
| NATO’s Arctic War Exercise Unites Climate Change and WWII (4.0) | Misinfo/Real |
| Eat Bugs! EU Pressing member States to Promote Climate Friendly Insect Protein Diets (4.0) | Misinfo/Misinfo |
| Coronavirus was created in Wuhan lab and released intentionally. (5.0) | Misinfo/Misinfo |

Table 4: News events that were labeled as misinformation by annotators and also given a high aggregated likelihood of being shared (spread). We show the predicted and gold labels.

<table>
<thead>
<tr>
<th>Label Type</th>
<th>Misinfo ↓</th>
<th>Real ↑</th>
<th>Effect size</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pred</td>
<td>2.040</td>
<td>3.240</td>
<td>0.764</td>
</tr>
<tr>
<td>Gold</td>
<td>2.531</td>
<td>3.213</td>
<td>1.380</td>
</tr>
</tbody>
</table>

Table 5: Likelihood of news events spreading, i.e. the annotators’ rating for how likely it is they would share the article based on the shown news event. For “Pred”, we ignore headlines where annotators were unsure about the label. For this and the following tables, arrows indicate the desired direction of the score. We use Cohen’s $d$ to compute effect size.

where $||$ represents concatenation.

For decoder-only models we also append the gold inference $y = g_1 \ldots g_N$, where $N$ is the length of the inference, and take the loss over the full sequence. All our models are optimized using cross-entropy loss, where for a sequence $t$:

$$CE(t) = -\frac{1}{|t|} \sum_{i=1}^{|t|} \log p_\theta(t_i | t_1, \ldots, t_{i-1}).$$

Here $P_\theta$ is the probability given a particular language model $\theta$.

6.2 Inference

We predict each token of the output inference starting from the topic token $s_t$ until the $[\text{eos}]$ token is generated. In the case of data with unknown topic labels, this allows us to jointly predict the topic label and inference. We decode using beam search.

7 Experiments

We first describe setup for experiments, as well as evaluation metrics for generation and classification experiments using our corpus (§7.2). In §7.3 and §7.4, we show the performance of large-scale language models on the task of generating Misinfo Reaction Frames and provide results for classification of news headlines.

7.1 Setup

We determine the test split according to date to reduce topical and news event overlap between train and test sets. We use the HuggingFace Transformers library for all experiments (Wolf et al., 2020). Hyperparameters are provided in Appendix A.7.

7.2 Evaluation Metrics

We compare reaction inference systems using common automatic metrics, including the BLEU (−4) ngram overlap metric (Papineni et al., 2002) and BERTScore (Zhang et al., 2020), a model-based metric for measuring semantic similarity between generated inferences and references. We use human evaluation to assess quality and potential use of generated writer intent inferences. Detailed explanations of criteria for human evaluation are given in Appendix A.5. For classification we report macro-averaged F1 scores.

7.3 Generating Reaction Frames

The automatic evaluation results of our generation task are provided in Table 6. We compare neural models to a simple retrieval baseline (BERT-NN) where we use gold implications aligned with the most similar headline from the training set. Results are mixed, but T5 model variants generally performed best. For human evaluation, we measure overall quality and perceived social acceptability of generated writer intents. We also measure the impact of the generated writer intent on perceived trustworthiness of news using a A/B testing study (See Appendix A.6 for setup details). We randomly sample model-generated “writer’s intent” implications from T5 models and GPT-2 large over 196 headlines where generated inferences were unique for each model type. We elicit 3 unique judgements per headline. Implications are templated in the form “The writer is implying that [implication]” for ease of readability.

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10 We use news articles from 2021 and the last two months of 2020 for the test set. We ensure there is no exact overlap between data splits.

11 Similarity is measured between headlines embedded with MiniLM, a distilled transformer model (Wang et al., 2020).

12 98 misinfo and 98 real headlines in the dev. set
<table>
<thead>
<tr>
<th>Model</th>
<th>Writer Intent</th>
<th>Reader Perception</th>
<th>Reader Action</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BLEU-4 ↑</td>
<td>BERTScore ↑</td>
<td>BLEU-4 ↑</td>
</tr>
<tr>
<td>BERT-NN</td>
<td>31.45</td>
<td>86.29</td>
<td>35.69</td>
</tr>
<tr>
<td>T5-base</td>
<td>51.48</td>
<td>88.03</td>
<td>31.98</td>
</tr>
<tr>
<td>T5-large</td>
<td>51.30</td>
<td>88.16</td>
<td>32.82</td>
</tr>
<tr>
<td>GPT-2 (small)</td>
<td><strong>60.68</strong></td>
<td>87.35</td>
<td><strong>37.22</strong></td>
</tr>
<tr>
<td>GPT-2 (large)</td>
<td>54.94</td>
<td>87.74</td>
<td>32.35</td>
</tr>
<tr>
<td>dev.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>test</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BERT-NN</td>
<td>34.46</td>
<td>86.35</td>
<td><strong>37.09</strong></td>
</tr>
<tr>
<td>T5-base</td>
<td>50.63</td>
<td>87.78</td>
<td>32.18</td>
</tr>
<tr>
<td>T5-large</td>
<td>50.86</td>
<td><strong>87.94</strong></td>
<td>32.89</td>
</tr>
<tr>
<td>GPT-2 (large)</td>
<td><strong>60.51</strong></td>
<td>87.73</td>
<td>34.18</td>
</tr>
</tbody>
</table>

Table 6: Automatic modeling results (generation task). For this table and the following tables, we highlight the best-performing model(s) in **bold**.

<table>
<thead>
<tr>
<th>Model</th>
<th>Quality (1-5)</th>
<th>+Trust (%)</th>
<th>-Trust (%)</th>
<th>Corr w/ Label (all gens)</th>
<th>Corr w/ Label (quality ≥ 3)</th>
<th>Socially Acceptable (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>T5-base</td>
<td>3.61</td>
<td>8.33</td>
<td>7.82</td>
<td><strong>0.24</strong>*</td>
<td>0.30*</td>
<td>75.30</td>
</tr>
<tr>
<td>T5-large</td>
<td><strong>3.74</strong></td>
<td>7.73</td>
<td>9.76</td>
<td>-0.03</td>
<td>0.09</td>
<td>74.66</td>
</tr>
<tr>
<td>GPT-2 (large)</td>
<td>3.46</td>
<td>9.70</td>
<td><strong>13.10</strong></td>
<td>-0.04</td>
<td><strong>0.10</strong></td>
<td><strong>74.66</strong></td>
</tr>
</tbody>
</table>

Table 7: Results of human evaluation (generation task). Correlations marked by “*” are statistically significant for p < .05.

<table>
<thead>
<tr>
<th>Model</th>
<th>Spread F1 ↑</th>
<th>Reader F1 ↑</th>
<th>Gold F1 ↑</th>
</tr>
</thead>
<tbody>
<tr>
<td>Majority Baseline</td>
<td>10.49</td>
<td>37.20</td>
<td>34.49</td>
</tr>
<tr>
<td>T5-base</td>
<td>22.77</td>
<td>77.72</td>
<td>87.13</td>
</tr>
<tr>
<td>dev.</td>
<td><strong>29.04</strong></td>
<td><strong>79.04</strong></td>
<td>88.12</td>
</tr>
<tr>
<td>T5-large</td>
<td>22.38</td>
<td>77.80</td>
<td>83.86</td>
</tr>
<tr>
<td>GPT-2 (small)</td>
<td>27.59</td>
<td>78.73</td>
<td>89.01</td>
</tr>
<tr>
<td>GPT-2 (large)</td>
<td>-</td>
<td>-</td>
<td>46.43</td>
</tr>
<tr>
<td>Prop-BERT</td>
<td>-</td>
<td>-</td>
<td>89.24</td>
</tr>
<tr>
<td>BERT-large</td>
<td>-</td>
<td>-</td>
<td>90.60</td>
</tr>
<tr>
<td>Covid-BERT</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Majority Baseline</td>
<td>11.20</td>
<td>35.07</td>
<td>38.58</td>
</tr>
<tr>
<td>T5-base</td>
<td>20.59</td>
<td>82.91</td>
<td>80.43</td>
</tr>
<tr>
<td>test</td>
<td><strong>30.60</strong></td>
<td><strong>84.95</strong></td>
<td>81.20</td>
</tr>
<tr>
<td>T5-large</td>
<td>18.41</td>
<td>82.70</td>
<td>81.35</td>
</tr>
<tr>
<td>GPT-2 (large)</td>
<td>-</td>
<td>-</td>
<td>38.79</td>
</tr>
<tr>
<td>Prop-BERT</td>
<td>-</td>
<td>-</td>
<td>79.80</td>
</tr>
<tr>
<td>BERT-large</td>
<td>-</td>
<td>-</td>
<td><strong>85.26</strong></td>
</tr>
<tr>
<td>Covid-BERT</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 8: Automatic modeling results (classification task).

We found that the T5-large model was rated as having slightly higher quality generations than the other model variants (Table 7). Most model generations were rated as being “socially acceptable”, however in as many as 25.34% of judgements, generations were found to be not acceptable. Interestingly, all models were rated capable of persuading readers to trust or distrust headlines, but effectiveness is dependent on the quality of the generated implication. For T5-large, we found a consistent correlation between the actual label and shifts in trust. Annotators reported that writer intents made real news appear more trustworthy and misinformation less trustworthy.

### 7.4 Detecting Misinformation

To test the limits of using stylometry to identify misinformation in our dataset, we predict the presence of rhetorical techniques commonly associated with propaganda in news event descriptions. For this, we use a pre-trained BERT propaganda detector (Da San Martino et al., 2019) which we denote here as Prop-BERT.\(^{13}\) For our zero-shot setting, we classify a news event as real if it is not associated with any rhetorical techniques and misinformation otherwise. As shown by table 8, F1 results are considerably lower than task-specific models. This is likely due to the fact both real and misinformation news uses rhetorical techniques.

Neural misinformation detection models are able to outperform humans at identifying misinformation (achieving a max F1 of 85.26 compared to human performance F1 of 75.21\(^{14}\)), but this is still a nontrivial task for large-scale models. When we use Covid-BERT (Müller et al., 2020), a variant of BERT pretrained on Covid-related tweets, we see an improvement of 5.46% over BERT without domain-specific pretraining (Table 8). This indicates...
Figure 3: Performance of fully unsupervised models and a MRF-finetuned GPT-2 model that was trained on a small number of cancer misinformation and real news examples.

Cates greater access to domain-specific data helps in misinformation detection, even if the veracity of claims stated in the data is unknown.

7.5 Performance on Out-of-Domain Data

We test the ability of Misinfo Reaction Frames to generalize using 100 cancer-related real and misinformation health news headlines (Cui et al., 2020), see Figure 3. For the misinformation detection task, we evaluate gold F1 using the Prop-BERT zero-shot model, MRF-finetuned BERT-large, Covid-BERT, T5-large and GPT-2 large models. We observe that generative MRF models (GPT2-large and T5-large) trained on all dimensions outperform BERT-large model in the unsupervised setting, consistent with the supervised setting. Notably, Prop-BERT achieves higher performance on the cancer subset than full MRF data.

We compare this performance against the GPT-2 large model further finetuned on only 574 cancer examples, and observe that this leads to a performance increase of 43.49%, achieving similar F1 performance to our domains with full data supervision.

Despite the domain shift, we find that MRF models are able to generate relevant inferences in an unsupervised setting. For example given the headline “fruits and veggies cut cancer risks.”, the GPT-2 large model generates the writer intent “people should eat more fruits and vegetables” and predicts readers will “feel hopeful”. However, there are some cases where unsupervised models make wrong predictions by confusing Covid, climate and cancer examples (e.g. predicting “covid-19 can be cured” as the writer intent for “miracle solution for cancer is actually bleach”). These are alleviated by the additional finetuning on a small number of examples (for the given example, GPT2-cancer correctly predicts the headline is misinformation and the writer intent as “there is a cure for cancer”).

8 Related Work

A number of definitions have been proposed for labeling news articles based on reliability. To scope our task, we focus on false news that may be unintentionally spread (misinformation). This differs from disinformation, which assumes a malicious intent or desire to manipulate (Fallis, 2014).

We design pragmatic frames, described in free-text implications which are invoked by a news headline. This follows prior work on pragmatic frames of connotation and social biases (Speer and Havasi, 2012; Rashkin et al., 2018; Sap et al., 2019, 2020; Forbes et al., 2020). Our formalism also builds upon the encoder-decoder theory of media (Hall, 1973), which proposes that before an event is communicated, a narrative discourse encoding the objectives of the writer is generated.

Rhetorical Framing of News. Prior work on rhetorical framing (e.g. Nisbet and Scheufele, 2009; Card et al., 2015; Field et al., 2018) has noted the significant role media frames play in shaping public perception of social and political issues, as well as the potential for misleading representations of events in news media. However, past formalisms for rhetorical framing that rely on common writing or propaganda techniques (e.g. appeal to fear or loaded language, Da San Martino et al., 2019) may not represent emerging trends in misinformation, particularly as real news becomes more sensationalized (Chakraborty et al., 2017, see §7.4 for zero-shot analysis of propaganda techniques). They also do not focus on the effectiveness of these techniques when used in practice. To that end, we propose a formalism focusing on readers’ perception of the writers’ intention, rather than specific well-known techniques.

Misinformation Detection. Prior work on detection of deceptive writing and misinformation has mostly focused on linguistic features (e.g. Ott et al., 2011; Rubin et al., 2016; Rashkin et al., 2017; Wang, 2017; Hou et al., 2019), as well as social network user interactions (Volkova et al., 2017; Jiang and Wilson, 2018). There has also been work on integration of knowledge graphs (Pan et al., 2018) and framing detection as a NLI task (Yang et al.,
Zellers et al. (2019) show the effectiveness of using large-scale neural language modeling to detect machine-generated misinformation. Recent work has also highlighted the importance of understanding the impact from misinformation, particularly in health domains (Dharawat et al., 2020; Ghenai and Mejova, 2018). Zhou and Zafarani (2020) and Hardalov et al. (2021) provide comprehensive surveys of misinformation detection methods. In contrast, we focus on the impact of readers’ prior beliefs on perception of news reliability. This is related to stance detection (Ghanem et al., 2018), however our pragmatic frames go beyond understanding the stance of a reader and explicitly capture how reader perceptions affect their actions.

**Countering Misinformation.** (Yaqub et al., 2020; Lai et al., 2020) show the effectiveness of credibility indicators to persuade readers to decrease their trust in false information. Prior work has also shown the effectiveness of social annotation alongside news for persuasion of readers (Kulkarni and Chi, 2013). In particular, (Jahanbakhsh et al., 2021) show that having users assess accuracy of news at sharing time and providing rationales for their decisions decreases likelihood of false information being shared. For future work, we consider use of Misinfo Reaction Frame rationales in real-time machine learning settings with additional contextual information like article sources.

**9 Conclusion**

We introduced Misinfo Reaction Frames, a pragmatic formalism for understanding reader perception of news reliability. We use these reaction frames to construct a corpus of news headline implications that explain potential interpretation and reaction of readers. We show that machine-generated reaction frames can used to change perceptions of readers, and while large-scale language models are able to discern between real news and misinformation, there is still room for future work. Generated reaction frames can potentially be used in a number of downstream applications, including better understanding of event causality, empathetic response generation and as counter narratives.

**10 Ethical Considerations**

There is a risk of frame-based machine-generated reader interpretations being misused to produce more persuasive misinformation. However, understanding the way in which readers perceive and react to news is critical in determining what kinds of misinformation pose the greatest threat and how to counteract its effects.

We emphasize that annotations may reflect perceptions and beliefs of annotators, rather than universal truths (Britt et al., 2019). Especially considering demographic homogeneity of online crowd-source workers, we urge caution in generalizing beliefs or taking beliefs held in certain social/cultural contexts to be factual knowledge. We obtained an IRB exemption for annotation work, and ensured annotators were fairly paid given time estimations.

**Broader impact.** The rapid dissemination of information online has led to an increasing problem of falsified or misleading news spread on social media like Twitter, Reddit and Facebook (Vosoughi et al., 2018; Geeng et al., 2020). New methods like Misinfo Reaction Frames aimed at understanding not only whether readers recognize misinformation but also how they react to it can help in mitigating spread.

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A

A.1 Annotator Statistics

We provided an optional demographic survey to MTurk workers during annotation. Of the 63 annotators who reported ethnicity, 82.54% identified as White, 9.52% as Black/African-American, 6.35% as Asian/Pacific Islander, and 1.59% as Hispanic/Latino. For self-identified gender, 59% were male and 41% were female. Annotators were generally well-educated, with 74% reporting having a professional degree, college-level degree or higher. Most annotators were between the ages of 25 and 54 (88%). We also asked annotators for news preferences. New York Times, CNN, Twitter, Washington Post, NPR, Reddit, Reuters, BBC, YouTube and Facebook were reported as the 10 most common news sources. The main task questions presented to annotators are given in Figure 4.

A.2 Additional Annotation Details

We include all annotations from qualified workers in the pilots and final task as part of the dataset, discarding annotations from disqualified workers. We also removed headlines that received no annotations due to deformities in the original text (e.g. unexpected truncation) or vagueness. We paid workers at a rate of $0.4 per hit during these pilots and $.6 per hit for the second stage pilot and final task.

For writer intent implications, we asked annotators if each of the 7 predefined themes was relevant to the event. If a theme was relevant, we asked annotators to provide 1-3 implications related to the chosen theme. For reader perception and action implications, we elicit 1-2 implications.

All news headlines are in English. The Poynter database contains international news originally presented in multiple languages, however news headlines contained in the database have all been translated into English.

A.3 Post-processing of Annotations

To remove duplicate free-text annotations, we check if annotations along the same MRF dimension have a ROUGE-2 (Lin, 2004) overlap of less than .8. If two annotations have a overlap that violates this threshold, we keep one and discard the other. We also remove writer intent annotations that have a ROUGE-2 overlap of greater or equal to .8 with the headline to prevent direct copying. Due to noise in the keyword filtering approach to labeling climate-related NELA-GT headlines, we remove headlines with specific keywords referencing toxic work environments or political climates.\(^{15}\)

Some “perception” annotations were more suited semantically to being “action” annotations or vice versa. If an “action” annotation is a single word categorized as a variant of a emotion word (Shaver et al., 1987), we reclassify it as a “perception.” Conversely, if a “perception” annotation includes “want,” expressing a desire for an action to happen or to do an action, we reclassify it as an “action.” During this process, we also remove single word annotations that feature common misspellings.\(^{16}\)

We restrict writer intent annotations to be at least three words long. Reader perception and action annotations must be at least three characters in length.

Finally, we handled missing free-text annotations. If a headline had no free-text annotations, we took this as an indicator of a low-quality example or assumed it lacked enough context for annotators to make a judgement. These invalid headlines were removed (8.5% of all headlines). If a writer intent annotation is missing, we assume the intent is ambiguous and mark it as “unknown intent.” These make up 6% of valid headlines and are not included in the overall count of implications. If a reader perception or action annotation is missing, we infer the corresponding implication from other annotated MRF variables using the strategy in Table 10.

A.4 Defining Reliability of News

In our framework, we focus on intent in terms of implications rather than questioning whether or not the writer’s intentions were malicious given that it is unclear the extent to which original writers might have known article content was misleading. We summarize common definitions for news reliability in Table 9).

A.5 Evaluation Metrics

A.5.1 Human Evaluation

For human evaluation, we assess generated inferences using the same pool of qualified workers who annotated the original data.

\(^{15}\)There may still be cornercases, but this covers the vast majority of mislabelings.

\(^{16}\)While misspellings were considered during overall quality control of workers, these are difficult to handle automatically. For example, automatic spell-checkers change instances of “biden” to “widen,” so we forgo automatic spellchecking.
<table>
<thead>
<tr>
<th>Type</th>
<th>Description</th>
<th>Covered by MRF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Misinformation</td>
<td>Misinformation is an umbrella term for news that is false or misleading.</td>
<td>✓</td>
</tr>
<tr>
<td>Disinformation</td>
<td>Unlike misinformation, disinformation assumes a malicious intent or desire to manipulate. In our framework, we focus on intent in terms of implications rather than questioning whether or not the writer’s intentions were malicious given that it is unclear the extent to which original writers might have known article content was misleading.</td>
<td>Potentially</td>
</tr>
<tr>
<td>Fake News</td>
<td>As defined by (Allcott and Gentzkow, 2017), fake news refers to “news articles that are intentionally and verifiably false, and could mislead readers.” (Golbeck et al., 2018) notes that fake news is a form of hoax, where the content is factually incorrect and the purpose is to mislead. This also overlaps with the definition of disinformation.</td>
<td>Potentially</td>
</tr>
<tr>
<td>Propaganda</td>
<td>Propaganda is widely held to be news that is “an expression of opinion or action by individuals or groups, deliberately designed to influence opinions or actions of other individuals or groups with reference to predetermined ends” (Miller, 1939). Propaganda is therefore wholly defined in terms of the intent of a writer or group of writers, and may contain factually correct content.</td>
<td>✓</td>
</tr>
<tr>
<td>Satire</td>
<td>We refer to articles written with a humorous or ironic intent as “satire.” We do not explicitly cover satire in MRF, but it is possible that some misinformation articles began as satire and were misconstrued as real news.</td>
<td>Potentially</td>
</tr>
<tr>
<td>Real (Trusted)</td>
<td>We consider this to be news that is factually correct with an intent to inform. We note that while real news is distinct from most of the article types shown here, it can also function as propaganda.</td>
<td>✓</td>
</tr>
</tbody>
</table>

Table 9: Article types based on intention and perceived reliability.

**Overall Quality**  We ask the annotators to assess the overall quality of generated inferences on a 1-5 Likert scale (i.e. whether they are coherent and relevant to the headline without directly copying).

**Influence on Trust**  We measure whether generated inferences impact readers’ perception of news reliability. We ask annotators whether a given generated inference makes them perceive the news headline as more (+) or less (-) trustworthy.

**Perceived Sociopolitical Acceptability**  We ask annotators to rate their perception of the beliefs invoked by an inference in terms of whether they represent a majority (mainstream) or minority (fringe) viewpoint\(^{17}\).

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\(^{17}\)We refer to “minority” viewpoint broadly in terms of less frequently adopted or extreme social beliefs (for example, viewpoints held by QAnon believers), rather than in terms of viewpoints held by historically marginalized groups.

### A.6 Human Evaluation Details

For A/B testing, annotators are initially shown the headline with the generated inference hidden. We ask annotators to rate trustworthy of headlines on a 1-5 Likert scale, with 1 being clearly misinformation and 5 being clearly real news. After providing this rating, we ask annotators to reveal the generated inference and rate the headline again on the same scale. Annotators were not told whether or not inferences were machine-generated, and we advised annotators to mark inferences that were copies of the headlines as low quality.
<table>
<thead>
<tr>
<th>Likelihood of Spread</th>
<th>Perceived Label</th>
<th>Randomly Sample from Choices</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;3 Misinfo</td>
<td>perception: ['feel lied to', 'feel disinterested', 'feel disbelief', 'feel this is false', 'feel suspicious']</td>
<td>action: ['fact-check this article', 'skip this article', 'check the facts', 'avoid sharing this article', 'do something else']</td>
</tr>
<tr>
<td>&lt;3 Real or Disagree</td>
<td>perception: ['feel unsure', 'feel like they need more information to process this']</td>
<td>action: ['move on to the next thing', 'read more', 'learn more']</td>
</tr>
<tr>
<td>&gt;3 Any</td>
<td>perception: ['feel curious', 'feel interested', 'feel like this is something others might want to know about']</td>
<td>action: ['talk to a friend about it', 'share the article', 'learn more', 'read more', 'try to understand']</td>
</tr>
<tr>
<td>=3 Any</td>
<td>perception: ['feel indifferent']</td>
<td>action: ['move on to something else']</td>
</tr>
</tbody>
</table>

Table 10: Process for handling missing reader annotations.

### A.7 Experimental Setup and Model Hyperparameters

All models are trained on either a single Quadro RTX 8000 or TITAN Xp GPU. Average training time for generative models ranges from approx. 1 hour per epoch for T5-base to 4 hours for GPT-2 large. Inference time for models ranges from approx. 10-20 minutes. Average training time for BERT models is approx. 30 minutes per epoch and inference time is approx. 10 minutes. We use a single final training/evaluation run and hyperparameters are manually tuned in the range of 1e-2 to 6e-6.

#### A.7.1 Classification

Supervised classification models are finetuned on our corpus. Both BERT and Covid-BERT models are trained for a maximum of 30 epochs with a learning rate of 1.5e-5 and batch size of 8. Propaganda detection models are trained using the settings given in (Da San Martino et al., 2019). BERT models have 345M parameters.

#### A.7.2 Generation

For GPT-2, models are finetuned with a learning rate of 2e-5. We use a learning rate of 5e-5 for T5. For all models except GPT-2 large we use a batch size of 16. For GPT-2 large we use a batch size of 4. We use beam search with a beam size of 3 for the generation task. Generation models are trained for a maximum of 10 epochs using early stopping based on dev. loss (in the case of the GPT-2 model finetuned on cancer data we finetune for a single epoch). We optimize using AdamW (Loshchilov and Hutter, 2019) and linear warmup. Model sizes range from 124M parameters for GPT-2 small to 774M parameters for GPT-2 large.
Figure 4: Layout of annotation task for collecting Covid-related MRF data.