

# A Truthfulness Stance Map for 2024 Election-Related Factual Claims.

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**Zhengyuan Zhu**

**Fifth year PhD supervised by Dr. Chengkai Li**

**Research focus: Natural Language Processing**

**The Innovative Data Intelligence Research Laboratory (IDIR Lab)**

# Problem Formulation



**"California introduces new bill that would allow mothers to kill their babies up to 7 days after birth."**



**POLITIFACT**



**"Florida has the highest homeowners insurance in the nation."**



# Truthfulness Stance Detection

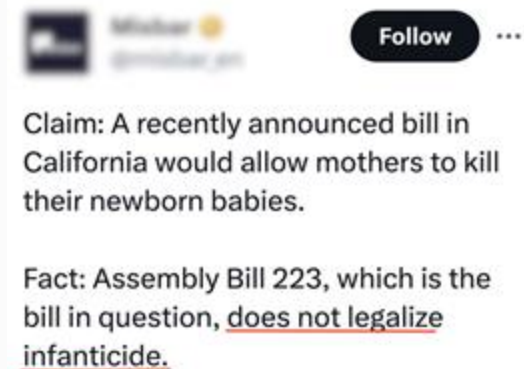


**"California introduces new bill that would allow mothers to kill their babies up to 7 days after birth."**

believes the claim is true

expresses a neutral stance

believes the claim is false

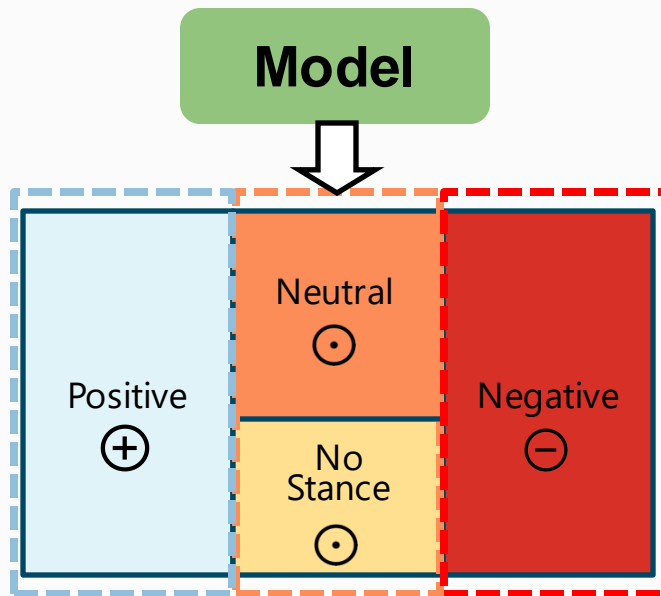
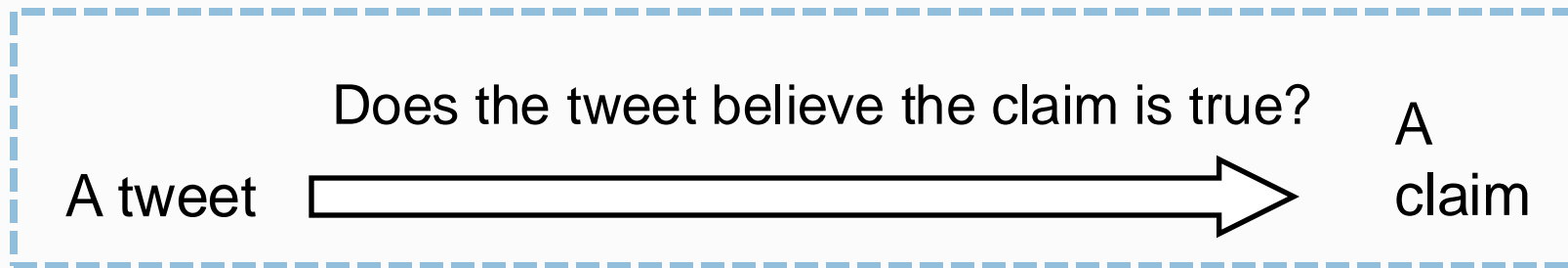


**Truthfulness stance detection: We detect the stance taken by tweets toward the truthfulness of factual claims.**

# Stance Detection Conceptual Framework

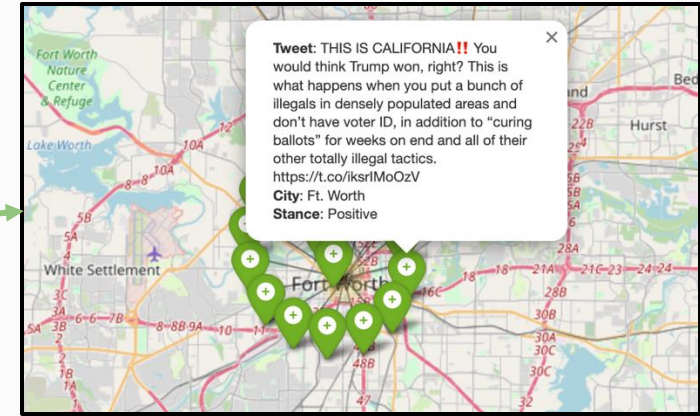
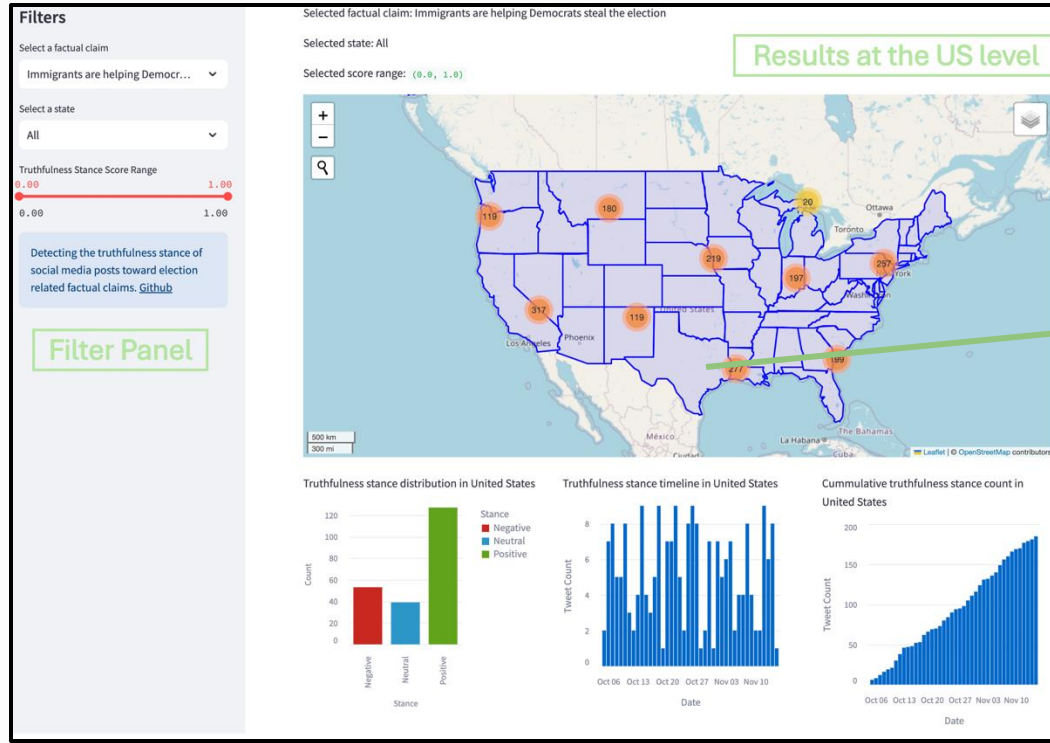
Type of stance	Target of stance			
	Entities or Topics	Events or Rumors	Fact Triples	Factual claims
Favorability	SemEval-2016; VAST; P-Stance; H-Stance	MGTAB	-	-
Likelihood	-	WT-WT	-	-
Truthfulness	-	PHEME; SemEval-2017; Semeval-2019	NewsClaims	Emergent; FNC-1; COVIDLies; TSD-CT

# Truthfulness Stance Detection



# Truthfulness Stance Helps Tackle Misinformation

- Gauge public perception toward factual claims
- Comprehend how misinformation spreads, e.g., identify susceptible communities.



**Thank you!**

# Backup Slides: Data Collection

## Fact-check collection

- We developed a tool to collect fact-checks from seven well-known fact-checking websites, including [AFP Fact Check](#), [AP Fact Check](#), [FactCheck.org](#), [FullFact](#), [Metafact](#), [PolitiFact](#), and [Snopes](#).

DataSource	AFP Fact Check	AP Fact Check	FactCheck.org	FullFact	Metafact	PolitiFact	Snopes
Claims	0*	297	0*	2,783	3,428	21,023	18,097
Review Summary	4,204	297	3,452	2,783	0*	21,023	2,638
Review	4,304	297	3,452	2,783	3,428	21,022	18,474
Verdict	0*	225	0*	0*	3,428	21,023	13,947



## Claim-tweet Pair Collection

1. We selected factual claims from PolitiFact in the fact-check collection, excluding those phrased as questions.
2. We then use [Spacy](#) to extract keywords (nouns, verbs, adjectives, pronouns, and numbers) from the claims.
3. For each factual claim, we retrieved related tweets via Twitter API v2 using a conjunctive (ANDed) query formed by the extracted keywords from the claim.
4. We filtered out tweets with fewer than 30 characters, as well as retweets, replies, and quotes, to avoid duplicates.
5. This process led to 36,154 claim-tweet pairs.

# Claim-tweet Pair Annotation

- [In-house annotation website](#)
- Annotators:
  - **96** annotators contributed to the annotation.
  - Their earnings were determined by the quality of their annotations, with the potential to earn up to 20 US cents for each claim-tweet pair they annotate.
- Quality control:
  - We used 287 carefully selected screening pairs. Each pair received consistent labeling from five researchers.
  - These pairs were mixed with the pairs that needed real annotation.
  - Annotators were scored based on how well their labels match the experts' labels on the screening pairs.
  - Annotations from low-quality annotators were excluded from the dataset.
  - Among all 206 annotators, 30 were deemed high-quality.

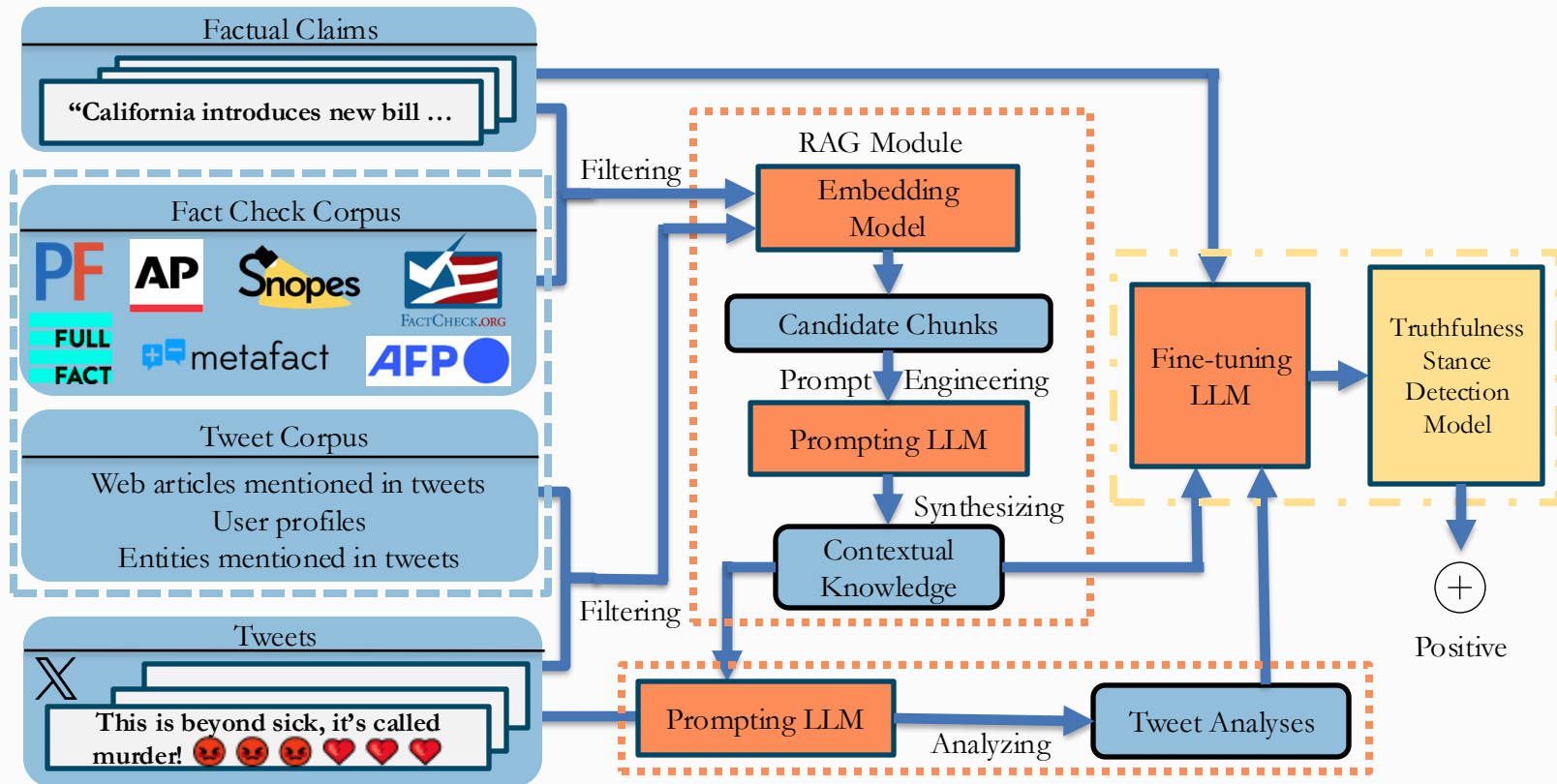
# TSD-CT Dataset

- Truthfulness stance detection for claim-tweet pair(TST-CT) dataset
- A total of 18,584 annotations were collected, with 13,594 from these high-quality annotators.
- This resulted in 3,105 completed pairs, containing 1,520 unique claims.
- Of the completed pairs, 216 were labeled as different topics and 669 as problematic.

$(\oplus)$	$(\odot)$	$(\ominus)$	Diff	Prob	Total
1,262	451	507	216	669	3,105

# RATSD Framework

## Retrieval Augmented Truthfulness Stance Detection



# Evaluation

We evaluated the performance of RATSD by comparing it to several state-of-the-art stance detection models, including fine-tuned LMs such as pre-trained model (BUT-FIT), generative pre-trained model (BLCU\_NLP), domain-adaptive pre-trained model (BERTSCORE+NLI, BART+NLI, and TESTED).

Model	TSD-CT				SemEval-2019				WT-WT				COVIDLies			
	$F_{\oplus}$	$F_{\odot}$	$F_{\ominus}$	$F_M$	$F_{\oplus}$	$F_{\odot}$	$F_{\ominus}$	$F_M$	$F_{\oplus}$	$F_{\odot}$	$F_{\ominus}$	$F_M$	$F_{\oplus}$	$F_{\odot}$	$F_{\ominus}$	$F_M$
BUT-FIT	83.38	72.00	65.11	80.11	49.09	50.98	92.01	64.03	81.29	94.73	79.29	85.10	47.62	97.82	23.53	56.32
BLCU_NLP	85.37	71.43	63.29	73.36	<b>70.15</b>	40.00	88.12	66.09	81.02	94.74	77.09	84.28	52.38	97.71	45.46	65.18
BERTSCORE+NLI	88.68	72.53	81.04	80.75	46.96	60.67	91.32	66.32	82.02	95.06	79.11	85.39	<b>57.14</b>	<b>98.20</b>	58.33	<b>71.22</b>
BART+NLI	88.00	73.42	74.25	78.56	47.96	51.71	91.90	63.86	82.82	95.52	81.75	86.70	50.00	98.00	<b>60.87</b>	69.62
TESTED	84.09	72.37	67.90	74.75	46.43	58.04	<b>92.08</b>	65.52	81.75	94.98	78.00	85.91	40.00	97.12	51.85	62.99
RATSD <sub>Zephyr</sub>	88.67	77.38	80.28	82.10	41.71	55.42	91.80	62.97	<b>83.85</b>	<b>95.72</b>	<b>82.66</b>	<b>87.44</b>	51.42	97.63	54.55	67.87
RATSD <sub>GPT-3.5</sub>	<b>93.27</b>	<b>80.24</b>	<b>87.90</b>	<b>87.13</b>	56.12	<b>63.79</b>	83.67	<b>67.86</b>	75.78	92.98	75.07	81.27	51.16	98.06	52.63	67.30