RATSD: Retrieval Augmented Truthfulness Stance Detection from Social Media Posts Toward Factual Claims

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Truthfulness Stance Detection

- Online information provides a valuable lens through which we can gauge people's perceptions and opinions, offering insights into societal trends, beliefs, and behaviors that shape human society.
- Truthfulness stance: given a factual claim, assesses whether a textual utterance affirms its truth, disputes it as false, or expresses a neutral or indeterminate position.
- Truthfulness stance has the potential to be a useful tool in discerning how misinformation spreads and shapes decision-making in political discourse and health-related contexts.

A Conceptual Framework for Stance

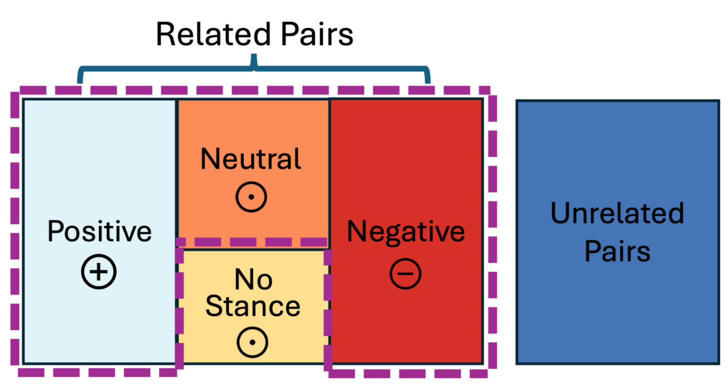
Type of Stance	Target of Stance: Entities or Topics	Events or Rumors	Fact Triples	Factual Claims
Favorability	SemEval-2016 (Mohammad et al., 2016); VAST (Allaway and Mckeown, 2020); P-Stance (Li et al., 2021); (Geimminger and Klinger, 2021); (Aleksandric el al., 2024)	MGTAB (Shi et al., 2023)		
Likelihood		WT-WT (Conforti et al., 2020)		
Truthfulness		PHEME (Zubiaga et al, 2016); SemEval-2017 (Derczynski et al., 2017); SemEval-2019 (Gorrell et al., 2019)	NewsClaims (Reddy et al., 2022); FactBank (Sauri and Pustejovsky, 2009); (Diab et al., 2009)	Emergent (Ferreira and Vlachos, 2016); FNC-1 (Pomerleau and Rao, 2017); COVIDLies (Hossain et al., 2020); This work (TSD-CT)

Utterance of Stance: ① news articles (in brown); ② social media posts (in blue).

Target of Stance: ① entities (e.g., Hillary Clinton) and topics (e.g., "legalization of abortion"); ② events (e.g., mergers and acquisitions of companies); ③ factual claims (e.g., news claims and news headlines) ④ fact triples extracted from the utterance itself.

Type of Stance: ① likelihood of target events occurring; ② favorability — determining whether the stance expressed in an utterance is in favor of or against a given target; ③ the truthfulness of a rumor, a news headline, a fact triple, or a claim.

Orientation of Stance: ① positive: a tweet conveys the belief that a claim is true; ② negative: a tweet believes a claim is false; ③ neutral/no stance: a tweet either expresses uncertainty about the truthfulness of a claim (neutral) or does not explicitly take a position on the claim's truthfulness (no stance).



TSD-CT Dataset

Fact-check Collection: Seven websites, 52,596 fact-checks (including associated factual claims) from 1995 to 2023.

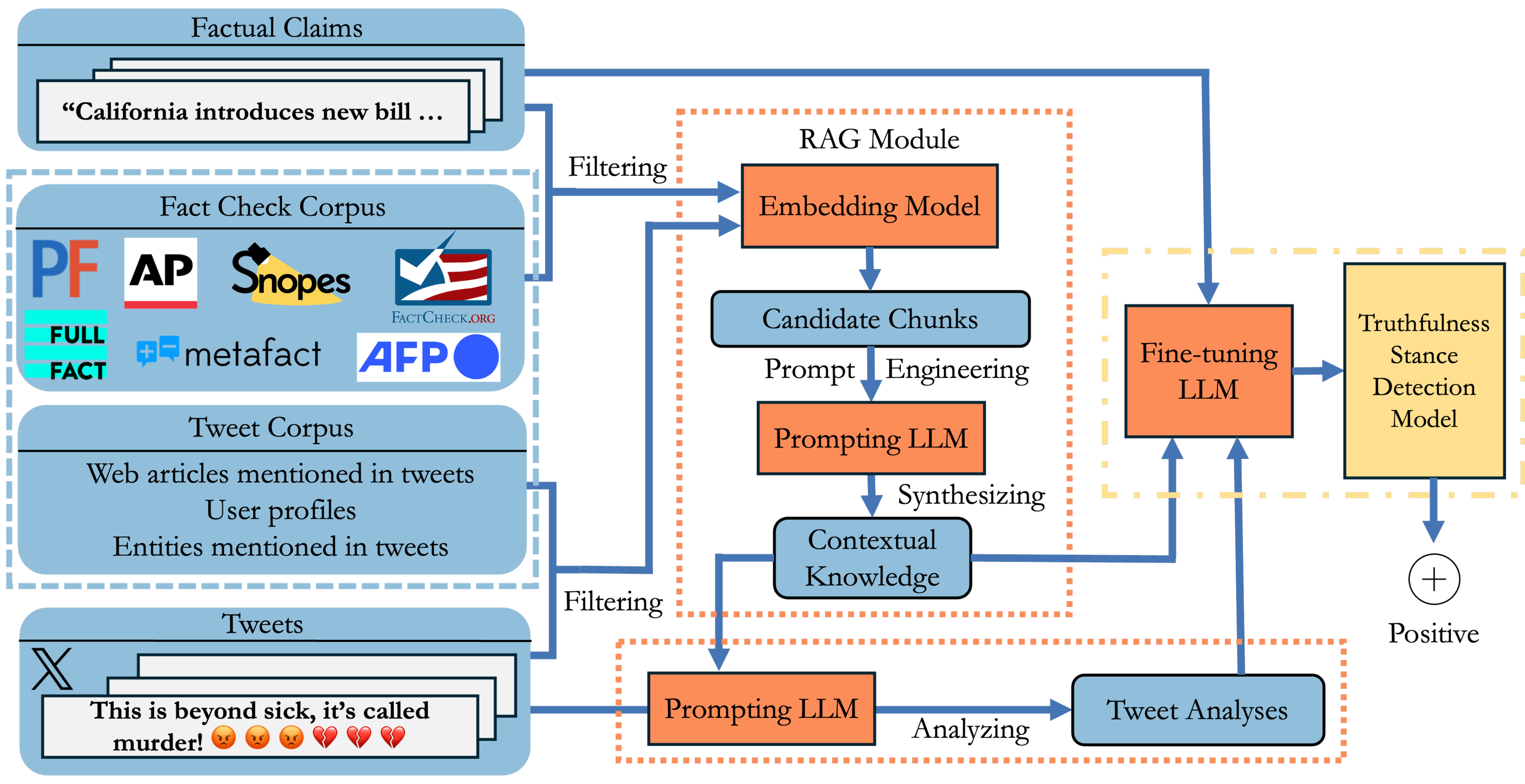
Claim-tweet Pair Collection:

- Extracted keywords from factual claims and retrieved related tweets using Twitter API v2, resulting in 36,154 pairs.
- After sanitization, retained 5,793 pairs for human annotation.

Claim-tweet Pair Annotation:

- In-house annotation website with detailed instructions, a progress monitoring page, and a leaderboard.
- Out of 206 annotators, 30 were deemed high-quality.
- Collected 3,105 annotated pairs containing 1,520 unique claims.

The RATSD Framework



Knowledge Corpora Construction: ① Factual claim knowledge corpus encompasses 52, 596 synthesized documents; ② Tweet knowledge corpus consists of 8, 236 synthesized documents from 2010 to 2023.

Contextual Knowledge Generation: (1) Document preprocessing (2) Relevant document selection (3) Relevant Chunk Retrieval (4) Prompting LLM

Stance Analysis: LLM is prompted using claim, tweet, contextual knowledge as the input to generate a narrative of tweet's truthfulness stance regarding claim.

Classification Model: LLM is fine-tuned using the claim-tweet pairs, stance analysis results, and contextual knowledge.

Evaluation

Our experiments used TSD-CT along with three benchmark datasets—SemEval-2019, WT-WT, and COVIDLies.

Dataset	⊕	⊙	⊖	Total
SemEval-2019	1,184 (13.8%)	6,784 (79.1%)	606 (7.1%)	8,574
WT-WT	6,663 (21.0%)	20,864 (65.7%)	4,224 (13.3%)	31,751
COVIDLies	670 (9.9%)	5,748 (85.1%)	340 (5.0%)	6,758
TSD-CT	1,262 (56.9%)	451 (20.3%)	507 (22.8%)	2,220

Model	TSD-CT $F_{\oplus}$	$F_{\odot}$	$F_{\ominus}$	F_M	SemEval-2019 $F_{\oplus}$	$F_{\odot}$	$F_{\ominus}$	F_M	WT-WT $F_{\oplus}$	$F_{\odot}$	$F_{\ominus}$	F_M	COVIDLies $F_{\oplus}$	$F_{\odot}$	$F_{\ominus}$	F_M
BUTFIT	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	**70.15**	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	**57.14**	**98.20**	58.33	**71.22**
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	**60.87**	69.62
TESTED	84.09	72.37	67.90	74.75	46.43	58.04	**92.08**	65.32	81.75	94.98	78.00	85.91	40.00	97.12	51.85	62.99
$RATSD_{Zephyr}$	88.67	77.38	80.28	82.10	41.71	55.42	91.80	62.97	**83.85**	**95.72**	**82.66**	**87.44**	51.42	98.63	54.55	67.87
$RATSD_{GPT-3.5}$	**93.27**	**80.24**	**87.90**	**87.13**	56.12	**63.79**	83.67	**67.86**	75.78	92.98	75.07	81.27	51.16	98.06	52.63	67.30

Fine-tuned Model Performance

- Both RATSD variants demonstrate strong performance across all datasets.
- $RATSD_{GPT-3.5}$ achieved the highest scores across all metrics on the TSD-CT dataset
- Different fine-tuned LLM in RATSD may excel in specific datasets or stance categories, which highlights the importance of model selection based on dataset characteristics.

Zero-shot Performance on TSD-CT

- $RATSD_{Zephyr\ zero}$ achieves the highest overall performance (F_M=36.55).
- $RATSD_{Zephyr\ zero}$ and $RATSD_{GPT-3.5\ zero}$ are better suited for zero-shot scenarios on the TSD-CT dataset.

Model	$F_{\oplus}$	$F_{\odot}$	$F_{\ominus}$	F_M
$BUT\text{-}FIT_{zero}$	12.82	0.00	33.88	15.56
$BLCU\_NLP_{zero}$	27.05	0.00	32.81	19.95
$BERTSCORE+NLI_{zero}$	6.82	**41.71**	17.65	22.06
$BART+NLI_{zero}$	33.55	50.58	3.96	26.03
$TESTED_{zero}$	**55.84**	38.91	4.04	32.93
$GPT\text{-}3.5_{zero}$	34.04	16.81	**39.74**	30.20
$RATSD_{Zephyr\ zero}$	49.74	32.14	27.78	**36.55**
$RATSD_{GPT-3.5\ zero}$	28.76	29.71	33.46	30.64

Ablation Study

- Stance analysis provides useful additional context for both positive and neutral pairs.
- Contextual knowledge generation is crucial in handling negative pairs.

Model	$F_{\oplus}$	$F_{\odot}$	$F_{\ominus}$	F_M
$RATSD_{Zephyr}$	**88.67**	**77.38**	80.28	**82.10**
w/o analysis	87.85	74.39	**81.01**	81.08
w/o context & analysis	87.16	75.15	78.01	80.11

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https://github.com/idirlab/RATSD

GitHub

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