Supplementary Material

Model	Multi Task Stance + Sentiment							
	Stance				Sentiment			
	Text		Text+Topic		Text		Text+Topic	
	Acc.	F1	Acc.	F1	Acc.	F1	Acc.	F1
Shared-only (SO)	2.61E-07	1.54E-06	1.20E-05	3.29E-05	3.72E-07	1.20E-05	0.00017	9.94E-06
Shared-Private (SP)	1.24E-06	0.0023	9.70E-06	0.00036	0.0014	0.00015	0.0027	5.05E-05
Shared-Private (SP) + Modality Specific Attn.	0.00029	0.00023	0.0084	0.00061	1.94E-06	1.87E-05	0.0017	0.00051
Shared-Private (SP) + Shared Specific Attn.	2.34E-05	0.0077	0.0021	0.0014	4.57E-06	6.16E-06	0.007	0.00836

Table 1: p-values of all the multi task variant models compared to the best performing SP-MT (Shared-Private + Modality Sp. Attn +Shared Sp. Attn)

Model	Multi Task Stance + Sentiment							
	Stance				Sentiment			
	Text		Text+Topic		Text		Text+Topic	
	Acc.	F1	Acc.	F1	Acc.	F1	Acc.	F1
Shared-only (SO)	1.58E+01	1.25E+01	9.55	8.32	1.36E+01	1.52	7.04	7.30
Shared-Private (SP)	1.29E+01	4.49	9.82	5.89	6.90	5.15	5.26	7.84
Shared-Private (SP) + Modality Specific Attn.	6.07	6.31	3.46	5.44	9.48	9.31	4.61	5.61
Shared-Private (SP) + Shared Specific Attn.	8.71	2.38	2.69	4.72	8.70	670	2.08	3.47

Table 2: T-test statistics of all the multi task variant models compared to the best performing SP-MT (Shared-Private + Modality Sp. Attn +Shared Sp. Attn)

1 Statistical Analysis

All results reported here are statistically significant, as we performed a t-test at the 5% significance level (Welch 1947). We also report the p-values and t-test statistics of all the multi-task variant models compared to the best performing multi-task model, i.e., SP-MT (Shared-Private + Feature-Specific Attention +Shared-Specific Attention), in Tables 1 and 2.

2 Dataset

The steps for the data collection and data annotation for the stance detection task are briefly described in Fig. 1. The data statistics is listed in Table 3.

2.1 Qualitative Aspect

Role of sentiment Tweet 1 in table 4 shows the importance of the prevailing sentiment, which helps to identify the tweets attitude towards climate change. The negative emotions of the tweet allow the model to focus on the words "busted", "idiotic" and "fraud" which at the same time help the stance detection task to understand that the tweet is against climate change. Similarly, for the tweet 2 in the believer category, the negative sentiment words like "worse" and "end" help the proposed model to focus on these words and associate them with the target word "climate crisis", which helps in identifying the believer attitude of the tweet. Tweet 3 shows that the stance detection task also improves the performance of sentiment analysis by helping the model to focus on words like "survived" which leads to the correct labelling of the neutral emotion of the tweet, although the presence of the word "no" could have guided the model to label the negative emotion. This shows that the multi-task approach, which uses both stance detection and sentiment analysis, plays an important role in increasing the performance of the model.

Dataset	Total Tweets	As per seed Hashtag		As per label prop. algo (out of seed hashtag)	
-	-	Denier	Believer	Denier	Believer
Harvard Data (Littman and Wrubel 2019)	1322969	1595	20886	1042	18421
Credibility Data (Samantray and Pin 2019)	9672907	4087	11225	2883	7735
Live tweets	5711743	10594	39787	9200	34274
Total tweets	-	16276	71898	13125	60430

Table 3: Dataset Statistics for Stance Detection Task

S.No.	Tweet	Stance	Sentiment
1.	MYTH BUSTED: Climate Change Consensus of Scientists Is Idiotic @scrowder #climatehoax #climatefraud	denier	negative
2.	This Climate Crisis is getting worse. We need to end it. #ClimateActionNow	believer	negative
3.	Polar bears survived periods when the Arctic had no ice at all... #ClimateChange #GlobalWarmingHoax	denier	neutral

Table 4: Role of Stance and Sentiment

2.2 Temporal Analysis

Fig. 2 shows the annual time trend of tweets from climate change deniers and proponents from 2009 to 2019, extracted from publicly available data. We note that the number of tweets prior to 2015 is very low, which could be due to the deletion of old tweets. However, the figure shows the in-

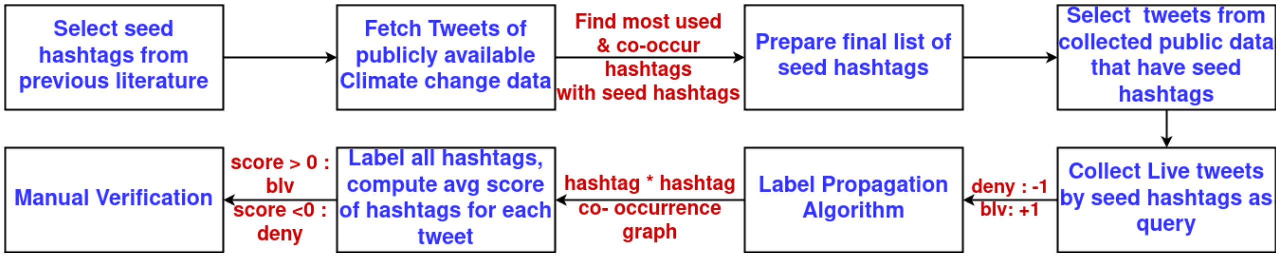

Figure 1: Steps of Data Collection & Annotation for Stance Detection Task

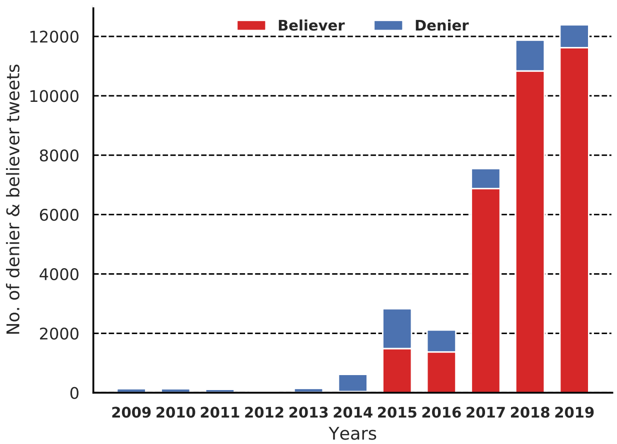

Figure 2: Number of believer and denier tweets per year

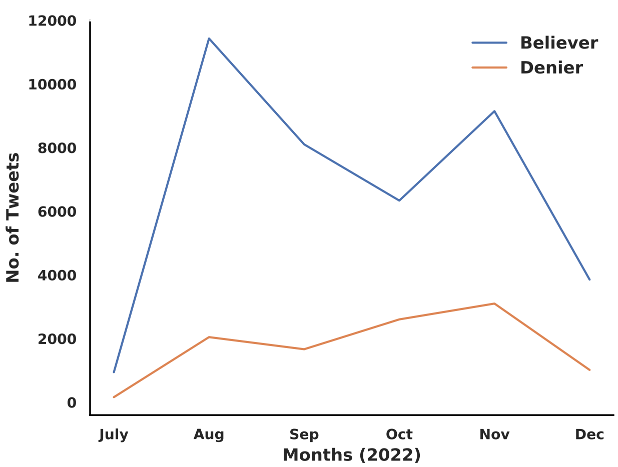

Figure 3: Number of believer and denier tweets per month of the 2022 year

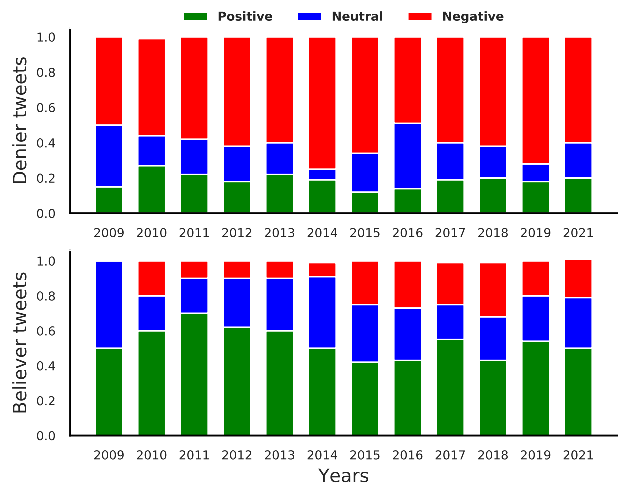

Figure 4: Ratio of sentiments in denier and believer tweets

creasing trend in the number of tweets from believers since 2015, which shows that people have started to believe in the climate crisis. In Fig. 3, we further analyse the monthly trend of the collected live data of 2022. The figure shows that the number of deniers increases from July to November. The maximum peak is observed in the month of November for both the believer and denier categories due to the UN Climate Change Conference (COP26)[1] summit held from October 31 to November 12, 2021. Although the number of denier tweets is lower than that of believers, the figure 4 shows the highest percentage of negative emotions in denier tweets across all years. Negative content dominates deniers tweets, often leading to the spread of false information about climate change to the public. The presence of such content led us to perform the task of classifying denier and believer tweets using sentiment analysis.

References

Welch, B. L. 1947. The generalization of ‘STUDENT’S’problem when several different population variances are involved. *Biometrika* 34(1-2): 28–35.

[1]https://ukcop26.org/