BERTweet's TACO Fiesta: Contrasting Flavors On The Path Of Inference And Information-Driven Argument Mining On Twitter

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Abstract

Argument mining, dealing with the classification of text based on inference and information, denotes a challenging analytical task in the rich context of Twitter (now 𝕏), a key platform for online discourse and exchange. Thereby, Twitter offers a diverse repository of short messages bearing on both of these elements. For text classification, transformer approaches, particularly BERT, offer state-of-the-art solutions. Our study delves into optimizing the embeddings of the understudied BERTweet transformer for argument mining on Twitter and broader generalization across topics. We explore the impact of pre-classification fine-tuning by aligning similar manifestations of inference and information while contrasting dissimilar instances. Using the TACO dataset, our approach augments tweets for optimizing BERTweet in a Siamese network, strongly improving classification and cross-topic generalization compared to standard methods. Overall, we contribute the transformer WRAPresentations and classifier WRAP, scoring 86.62% F1 for inference detection, 86.30% for information recognition, and 75.29% across four combinations of these elements, to enhance inference and information-driven argument mining on Twitter.

1 Introduction

Twitter (now 𝕏) is a global hub for opinions, news and information and serves as a primary data source for research, which had already recognized the value of its user-generated content prior to its transition to 𝕏 (Kwak et al., 2010; Boyd et al., 2010; Castillo et al., 2011).

Argument Mining is primarily about text classification, considering the structure of arguments, encompassing both informative and inferential elements (Palau and Moens, 2009; Peldszus and Stede, 2013; Lawrence and Reed, 2019).

For text classification, the pre-trained transformer BERT (Devlin et al., 2019) and its numerous domain-specific derivatives, such as BERTweet (Nguyen et al., 2020), achieve state-of-the-art performance (Houlsby et al., 2019; Sun et al., 2019) with a soft-max classification head added as additional layers. During the fine-tuning process, such transformers are used to generate universal text representations serving as contextualized language features to inform the head, which in turn are further specialized for the actual downstream task.

Thereby, the field of argument mining has also witnessed the benefits of transformer models like BERT for cross-topic classification (Bhatti et al., 2021; Thorn Jakobsen et al., 2021) and argument similarity (Reimers and Gurevych, 2019; Reimers et al., 2019; Thakur et al., 2021) on the AFS (Misra et al., 2016), UKP (Stab et al., 2018), and IBM-Debater (Shnarch et al., 2018) corpus.

Besides the common methods of adjusting the in-task performance through parameter tweaks (Lan et al., 2019; You et al., 2019) or incorporating augmentations (Kaushik et al., 2019; Anaby-Tavor et al., 2019; Feng et al., 2021; Thakur et al., 2021), multi-task learning is recommended as an additional fine-tuning strategy (Sun et al., 2019; Stab et al., 2018). Thereby, multi-task learning denotes a prior phase of fine-tuning representations on auxiliary tasks such as clustering or semantic similarity before proceeding to the actual classification step and is argued to effectively reduce a model's sensitivity to spurious correlations (Liu et al., 2019; Tu et al., 2020), which in turn is key to cross-topic argument mining (Thorn Jakobsen et al., 2021).

We believe that acquiring robust and meaningful representations, in the sense of perceiving the constituent elements of arguments, prior to classification is particularly useful for the nuanced task of argument mining when applied to diverse topics.

Generalizability in terms of cross-topic classification is crucial for practical argument mining in realistic scenarios, both in general research (Daxenberger et al., 2017; Stab et al., 2018) and specifically on Twitter (Schaefer and Stede, 2021), necessitating models to focus on argument components while avoiding reliance on spurious correlations like topic words (Thorn Jakobsen et al., 2021).

In this paper, we pioneer the optimization of the understudied transformer BERTweet for argument mining on Twitter. Thereby, we refine its linguistic knowledge of tweets within the embedding space, specializing BERTweet to better encode inference and information across diverse topics.

Utilizing the TACO dataset (Feger and Dietze, 2023), offering initial baseline evaluations of BERTweet for argument mining on Twitter, we optimize the model's representation layers in a multi-task approach by accentuating the contrast between inference and information while centering similar manifestations before the actual classification step.

We achieve this by configuring a Siamese BERTweet network using SBERT (Reimers and Gurevych, 2019). Applying contrastive loss (Hadsell et al., 2006) and text augmentation techniques (Wei and Zou, 2019), this network teaches BERTweet to cluster tweet embeddings according to their respective roles in argument mining, that is, to generally encode the presence or absence of both inference and information in the final representations for classification.

Utilizing BERTweet's enhanced embeddings, it excels in both closed and cross-topic argument mining on Twitter, outperforming standard methods (Schaefer and Stede, 2021) in this domain.

Towards inference and information-driven argument mining on Twitter, we contribute[1]:

- A pre-classification fine-tuning approach for BERTweet, enhancing its capacity to encode information and inference for closed and cross-topic argument mining on Twitter.
- An augmentation strategy to reduce spurious entity and topic signals while increasing sentence variability in tweets.
- WRAPresentations[2], an enhanced BERTweet embedding model driven by inference and information, achieved through contrastive optimization on augmented TACO tweets.
- WRAP[3], our tweet argument classifier leveraging WRAPresentations for argument mining across diverse topics on Twitter.

[1]Code: anonymous.4open.science/r/TACO-Fiesta
[2]huggingface.co/TomatenMarc/WRAPresentations
[3]huggingface.co/TomatenMarc/WRAP

2 Twitter Arguments from Conversations

Our primary dataset, TACO (Feger and Dietze, 2023), encompasses 1,734 tweets from 200 entire conversations spanning six topics: #Abortion (25.9%), #Brexit (29.0%), #GOT (11.0%), #LOTRROP (12.1%), #SquidGame (12.7%), and #TwitterTakeover (9.3%). So far, it stands as the sole publicly available labeled tweet dataset tailored for conversation-level inference and information extraction, strategically addressing reply-pattern nuances inherent to their conversational contexts.

Annotations were conducted by six experts according to the Cambridge Dictionary[4] definitions, differentiating *inference* as *a guess that you make or an opinion that you form based on the information that you have* and *information* as *facts or details about a person, company, product, etc.*. With a robust agreement of 0.718 Krippendorff's α, four classes emerged of these elements: *Reason* (inference and information), *Statement* (inference without information), *Notification* (information without inference), and *None* (neither element).

Table 1 details the class distribution of TACO.

Reason	Statement	Notification	None
581 (33.50%)	284 (16.38%)	500 (28.84%)	369 (21.28%)

Table 1: The class distribution of tweets in TACO.

On TACO, Vanilla BERTweet serves as the best performing baseline, excelling with 74.45% F1 for Reason, 56.66% F1 for Statement, 78.30% F1 for Notification, and 80.56% F1 for None after fine-tuning on these classes (Feger and Dietze, 2023).

3 Inference and Information-Driven Representations for Mining Arguments

In text classification, transformers like BERTweet use the final hidden state of the first token $[CLS]$ as the sequence representation. Classification involves a soft-max classifier added as an extension after the final representation layer, determining label probabilities for a tweet t by evaluating the likelihood of assigning a label y as:

$$p(y|h) = softmax(\hat{W}h) \quad (1)$$

where, $\hat{W}$ signifies the task-specific weights of the classification head, and h represents the final representation of t obtained with the transformer. Achieved through pooling an entire sequence representation via $[CLS]$, h is expressed as

[4]dictionary.cambridge.org

$G_W(t) = h$, where the transformer is considered an independent function $G_W(t)$ with its distinct weights W, taking t as input. For the specific classification task, both $\hat{W}$ and W are jointly fine-tuned by maximizing the log-probability of the correct label, where h implicitly undergoes optimization.

For optimizing class assignments on TACO, we emphasize the impact of specializing h for encoding inference and information before classification.

Hence, we consider the pre-classification specialization of an embedding h as a contrastive problem of semantic similarity, where tweets with similar expressions of the text dimensions inference and information are brought closer together, while those lacking in similarity are positioned farther apart.

3.1 Embedding Inference and Information

We measure the semantic similarity between two tweet representations, denoted as h_1 and h_2, using cosine distance:

$$D(h_1, h_2) = 1 - cos(h_1, h_2) \in [0, 2] \quad (2)$$

a standard metric (Mikolov et al., 2013; Kim, 2014; Tai et al., 2015; Chen and He, 2020) for assessing text vector similarity. $D(h_1, h_2)$ reflects complete equivalence at 0, orthogonality at 1, and absolute dissimilarity at 2. Mainly defined by the cosine similarity $cos(h_1, h_2) \in [-1, 1]$, where -1 represents complete dissimilarity, 1 indicates equivalence, and values closer to 0 suggest orthogonality, this distance is length-independent and primarily influenced by the angle between two embeddings.

Building on this circumstance, we assume that the actual representation h of a tweet can be normalized and lies on the n-sphere:

$$S(n) = \{h \in \mathbb{R}^{n+1} : \|h\| = 1\} \quad (3)$$

Transferred to the Cartesian nature of arguments $h = \langle inference, information \rangle$, we consider their representations to live on the unit sphere $h \in S(1)$ (Wang and Isola, 2020; Khosla et al., 2020; Chen and He, 2020). In h, 1 signifies full presence, and -1 implies total absence of a component. Consequently, an ideal class center on the unit sphere heads towards the pole $\langle 1, 1 \rangle$ for Reason, $\langle 1, -1 \rangle$ for Statement, $\langle -1, 1 \rangle$ for Notification, and $\langle -1, -1 \rangle$ for None. A breakdown of this is shown in the upper part of Figure 1, acknowledging the realistic expectation that the actual embeddings may differ from the ideals while the objective is to get them closer to them.

3.2 Contrastive Siamese Network

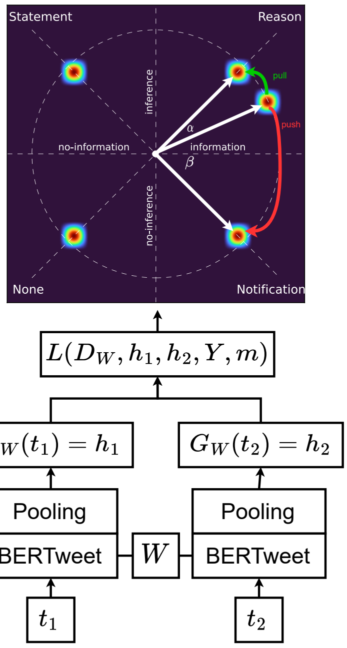


Figure 1: Visualization of the employed Siamese BERTweet architecture, with parameterized cosine distance $D_W(h_1, h_2)$ and contrastive loss $L(D_W, h_1, h_2, Y, m)$. Atop this architecture, the Cartesian embedding space for an argument representation $h = \langle inference, information \rangle$ is presented as target.

To address semantic similarity, a prevalent strategy involves enhancing representations through learning a metric (Chopra et al., 2005; Xing et al., 2002; Hadsell et al., 2006). Precisely, metric learning entails the implicit acquisition of a metric $D_W(h_1, h_2)$ parameterized by the weights W of the representation model G_W (Chopra et al., 2005). We seek to find W such that the target metric:

$$D_W(t_1, t_2) = 1 - cos(G_W(t_1), G_W(t_2)) \quad (4)$$

is smaller if t_1, t_2 are semantically similar, and higher if not.

By utilizing the identical embedding function $G_W(t)$ (BERTweet) with shared weights W to learn the metric, our architecture is referred to as a Siamese network (Bromley et al., 1993; Chopra et al., 2005). Similar and dissimilar tweet pairs are provided as input to this network. To update the weights and optimize the network's performance, a loss function is applied on top of this architecture.

To attain the goal of increasing the differentiation between similar and dissimilar pairs, it is suggested to employ the contrastive loss (Chopra et al., 2005; Hadsell et al., 2006):

$$L(D_W, h_1, h_2, Y, m) = (Y)\frac{1}{2}D_w(h_1,h_2)^2 + (1-Y)\frac{1}{2}\{max(0, m - D_w(h_1,h_2))\}^2 \quad (5)$$

where, h_1, h_2 are two representations ($G_W(t_i) = h_i$) of different tweets t_1, t_2 to be optimized given $D_W(h_1, h_2)$ as metric. Y denotes the binary label indicating if t_1, t_2 are similar ($Y = 1$) or contrasting ($Y = 0$). Furthermore, a margin value $m > 0$ is introduced as the minimal distance between two contrasting tweets.

When establishing m, our objective was to set $D_W(h_1, h_2)$ in a way that maximizes contrast between dissimilar pairs while avoiding overestimation of their true distance. Focusing on $D_W(h_1, h_2) \in [0, 1]$, representing positive similarity, we selected $m = 0.5$. This choice intuitively represents the minimum threshold for high similarity, yielding optimal results in our study.

With $m = 0.5$ we ensure that even if a representation closely matches an ideal center but is labeled as dissimilar, the optimized representation pushes $60°$ away and into an adjacent quadrant.

3.3 Augmentation of TACO

In the initial phase of processing TACO data, we generated a unique copy for each tweet through augmentation, denoted as A-TACO. Employing EDA (Easy Data Augmentation) techniques (Wei and Zou, 2019) of (1) synonym replacement, random (2) insertion, (3) swap, and (4) deletion, this procedure segregates our total ground truth into A-TACO, for optimization the embedding space of BERTweet prior to classification, and TACO, designated for fine-tuning and evaluating classifiers.

Maintaining independence between optimization and evaluation data is crucial to avoid spurious correlations (Thorn Jakobsen et al., 2021) and ensure that the data includes essential signals for class representations, thus enabling broad generalization across varying sentence structures and cross-topic evaluations for classifiers.

Following technique (1), we utilized spaCy[5] to identify all entities and specific words related to the six topics in the TACO dataset. Subsequently, we replace these words with the $[MASK]$ token, a placeholder commonly used by BERT-like models, including BERTweet, for predicting missing words.

[5] https://spacy.io

In particular, we utilized BERTweet as a fill-mask model to generate new tokens for those masked in the input sequence (Kumar et al., 2020).

To introduce word choice variability while minimizing semantic changes, random replacement of 10-90% of all words is applied using techniques (2-4). The optimal coherence, indicated by an average cosine distance of ~0.08 between the $[CLS]$ tokens of tweets and augmentations, is observed at a 10% replacement rate, maintaining overall semantic consistency while increasing sentence variability. Again, step 1 is applied to avoid reintroducing topic words. An example of the resulting tweet augmentation is shown in Table 2.

TACO	**Elon Musk** ready with 'Plan B' **if Twitter** rejects his offer **Read @USER Story | HTTPURL #ElonMusk #ElonMuskTwitter #TwitterTakeover HTTPURL**
A-TACO	**Wenger** ready with 'Plan B' **as Wenger** rejects his offer **- HTTPURL via @USER**

Table 2: An augmented Notification demonstrating entity replacement, topic word removal related to #TwitterTakeover, and altered sentence structure for enhanced anonymity, particularly at the end.

4 Experimental Setup

This section outlines the protocols used for evaluating and optimizing BERTweet's embedding space with A-TACO and follow-up classification on TACO. Our primary objective is to acquire enhanced semantic similarity, with a specific emphasis on overall F1, while considering recall for generalizability to unseen topics.

4.1 Models

In our approach, it is important to differentiate between the pre-classification fine-tuning for specializing embeddings and their subsequent fine-tuning tailored for mining arguments on TACO.

For both tasks, we utilize the Vanilla BERTweet model[6], with 12 transformer blocks and 12 self-attention heads processing sequences of up to 128 tokens, consistent with the baseline evaluation model of TACO (Feger and Dietze, 2023).

The embedding model BERTweet, enhanced through the application of contrastive loss within the Siamese network using A-TACO, is referred to as WRAPresentations.

Distinct from our multi-task approach, we introduce Augmented BERTweet, which undergoes

[6] huggingface.co/vinai/bertweet-base

pre-classification fine-tuning using the same tweets of A-TACO as WRAPresentations but directly optimizes $p(y|h)$ through standard cross-entropy loss.

For classification on TACO, we utilize TF-IDF representations, where word frequency is widely recognized as a feature in strong baselines for argument mining on Twitter, which are Support Vector Machine (SVM) (Addawood and Bashir, 2016), Logistic Regression (LR) (Bosc et al., 2016; Dusmanu et al., 2017), and Random Forest (RF) (Dusmanu et al., 2017). These models go beyond considering individual words by incorporating tweet-related features like emoji, URL, and hashtag frequencies. Despite this, their potential for cross-topic generalizability remains unexplored.

For each classifier, we evaluate the average class length for classification to examine linguistic feature acquisition.

4.2 Pre-Classification Fine-Tuning

To enhance BERTweet's embeddings, we chose TACO's golden tweets with flawless annotation agreement, accounting for 70.30% of all tweets, with class distribution remaining largely consistent.

For the final evaluation, we employ original golden tweets for #Abortion but augmentations of golden tweets for the remaining five topics during fine-tuning. #Abortion is chosen as the holdout topic due to its highest dissimilarity when compared to the remaining topics, posing a greater challenge for classification (Thorn Jakobsen et al., 2021). This provides initial insights into cross-topic generalization and the efficacy of fine-tuning with augmentations and predicting given real tweets. Pairs are formed for all tweet combinations, denoting tweets of the same class as similar $Y = 1$ and those of different classes as dissimilar $Y = 0$, yielding more dissimilar than similar pairs.

For the final validation set, 86,142 pairs were generated. The optimization data, divided into fine-tuning and test sets with a stratified $60/40$ ratio, yielded 307,470 and 136,530 candidate pairs, respectively. To ensure a balance between similar and dissimilar pairs, we chose the largest possible set such that both similar and dissimilar pairs are equally represented (Bromley et al., 1993; Chopra et al., 2005) while maintaining all tweets of the respective splits.

In total, 162,064 pairs were obtained for fine-tuning, 71,812 for testing, and 53,560 for final validation of the enhanced BERTweet representations prior to classification.

For all transformer models, we performed fine-tuning over 5 epochs using an A100 GPU with 40GB of memory, a batch size of 32, and a learning rate of $4e^{-5}$, which proved to be optimal for all models. The Siamese BERTweet network is implemented using SBERT (Reimers and Gurevych, 2019) as depicted in the lower part of Figure 1.

Additionally, we performed fine-tuning on WRAPresentations using both $[CLS]$ pooling, later employed for classification, and $[MEAN]$ pooling, which is recommended for improved sentence embeddings (Reimers and Gurevych, 2019).

4.3 Argument Mining on TACO

We evaluate the practicality of BERTweet's specialized embeddings on TACO, given the three argument mining tasks of (1) inference detection, (2) information recognition, and (3) classification of all four tweet classes, with a concurrent aim for cross-topic generalization.

For task (3), we trained a feed-forward neural network with two linear layers on top of each embedding model, undergoing 5 additional fine-tuning epochs with the best performing parameters having a learning rate of $4e^{-5}$ and batch size of 8, corresponding to the best model and parameters reported for TACO (Feger and Dietze, 2023). Again, we used a single A100 GPU with 40GB of memory. Thereby, the results for tasks (1) and (2) are aggregations specific to class elements of task (3) predictions, focusing on inference or information.

Our classifier evaluation uses two distinct configurations to examine the impact of specialized embeddings and their adaptability to additional class adjustments (Peters et al., 2019).

In the first setup (Frozen), freezing embeddings allowed us to assess the benefits attributable to pre-classification fine-tuning. In the second setup (Dynamic), embeddings underwent further fine-tuning during classification head optimization, where we assessed their adaptability to task-specific learning. Success in this context signifies a model's ability to leverage knowledge encoded in fine-tuned embeddings before classification and adapt them to the classes specific to inference and information.

We employed a 6-fold shuffled cross-validation, maintaining consistent splits for all classifiers across the six topics of TACO, to establish an upper-bound (Thorn Jakobsen et al., 2021). This closed-topic validation was then compared with cross-topic validation, where each of the six topics served as a unique testing set, and the remaining five topics were utilized for fine-tuning (Bosc et al., 2016; Daxenberger et al., 2017; Stab et al., 2018). Lower performance is expected in cross-topic validation, as classifiers are exposed to unseen topics.

5 Results

In this section, we assess the impact of the specialized embeddings for closed and cross-topic classification on TACO.

5.1 Results Pre-Classification Fine-Tuning

Model	P	R	F1
Vanilla BERTweet-$[CLS]$	50.00	100.00	66.67
Augmented BERTweet-$[CLS]$	65.69	86.66	**74.73**
WRAPresentations-$[CLS]$	**66.00**	84.32	74.04
WRAPresentations-$[MEAN]$	63.05	**88.91**	73.78

Table 3: Evaluating within-class similarity and between-class separability of fine-tuned $[CLS]$ representations on A-TACO towards TACO's holdout topic #Abortion. WRAPresentations, with $[MEAN]$ pooling in fine-tuning, show pessimistic scores but achieve a higher F1 score of 74.07% if tested with $[MEAN]$ pooling.

After pre-classification fine-tuning to enhance semantic similarity, we evaluate the optimized embedding models for classifying tweet pairs as similar or dissimilar given $D_W(t_1, t_2)$.

All fine-tuning strategies outperformed Vanilla BERTweet in terms of F1, compare Table 3.

We excluded WRAPresentations with $[CLS]$ pooling for follow-up classification due to the absence of discernible benefits in F1 compared to Augmented BERTweet and WRAPresentations using $[MEAN]$ pooling for pre-classification fine-tuning, also showing a higher recall at 88.91%.

Hence, we will refer to WRAPresentations-$[MEAN]$ as WRAPresentations.

In comparing Augmented BERTweet and WRAPresentations, both models show similar overall performance in terms of F1, but diverge in their emphasis on precision and recall. The results suggest that contrastive fine-tuning of representations is not inherently superior to directly optimizing $p(y|h)$ with augmented tweets. However, this strategy enhances recall, with further distinctions expected in downstream task evaluations.

Nonetheless, we assume that the enhanced recall at this stage is already a first indicator for later generalizations of classifications across topics. Additionally, we confirmed the effectiveness of pre-classification fine-tuning with A-TACO when applied to real tweets from an unseen topic.

Furthermore, we visually explored BERTweet's embedding space before and after fine-tuning, utilizing $[CLS]$ representations of all original tweets in TACO, as depicted in Figure 2(a).

Applying t-SNE for dimensional reduction (van der Maaten and Hinton, 2008; Jawahar et al., 2019), comparing Vanilla BERTweet with WRAPresentations showed enhanced class quadrant density, compare Figure 2(a), suggesting an improvement of class semantics given inference and information for a majority of tweets. Similar patterns, albeit at smaller numbers, are observed for Augmented BERTweet, see Figure 2(b).

Numerically, WRAPresentations improved tweet order by 38% for Reason, 37% for Statement, and 41% for Notification over Vanilla BERTweet. Despite a -2% decrease in the None class quadrant, it remains predominant, as shown in Figure 2(b).

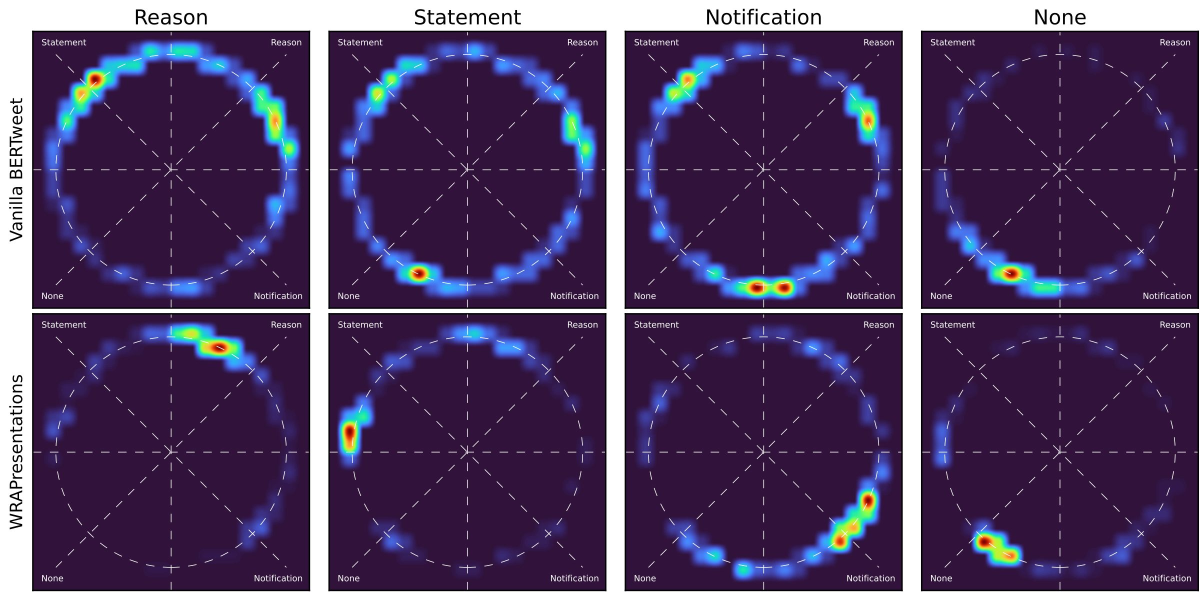
Augmented BERTweet closely matches WRAPresentations, excelling by 6% for None but lagging behind by -6% for Reason, -12% for Statement and -13% for Notification.

5.2 Results Classification and Generalization

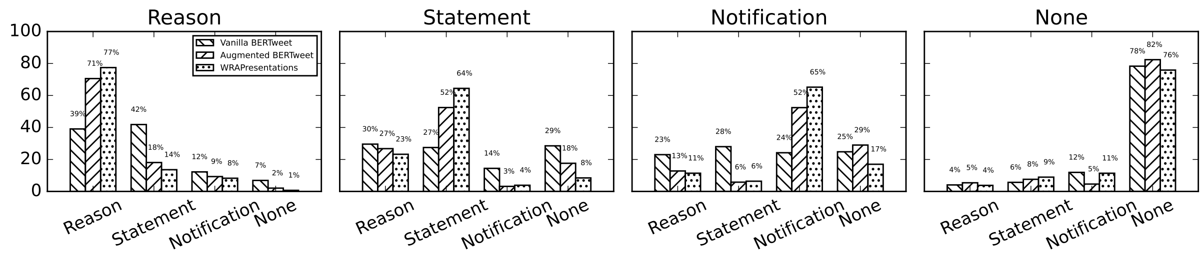
For our comparisons, we continue to present the outcomes of the Random Forest classifier as the most effective baseline and the average class length as a minimal-performance indicator. Furthermore, for publication, we refer to the classifier based on WRAPresentations as WRAP, while maintaining the term WRAPresentations for consistency.

When turning to the closed-topic validation, WRAPresentations outperforms all classifiers except task (1), where dynamic embeddings in Augmented BERTweet exhibit performance nearly equivalent, as demonstrated in the upper half of Table 4. Quantitatively, WRAPresentations yields 86.88% F1 for task (1), 81.54% F1 for task (2), and 71.07% F1 for task (3) when frozen. Dynamically optimizing embeddings, WRAPresentations achieves 86.62% F1 for task (1), 86.30% F1 for task (2), and 75.29% F1 for task (3).

Shifting our attention to the more demanding task of cross-topic validation, assessing a classifier's ability to generalize to unseen topics, WRAPresentations demonstrates superior performance over all evaluations, thereby achieving 86.83% F1 for task (1), 81.54% F1 for task (2), and 70.93% F1 for task (3) when frozen. With dynamically adjusted embeddings, it achieves 86.27% F1 for task (1), 84.90% F1 for task (2), and 73.54% F1 for task (3), compare lower half of Table 4.



(a) t-SNE embeddings of tweet class $[CLS]$ tokens before and after fine-tuning given inference and information.



(b) Distribution of classes within the projected quadrants of the expected $\langle inference, information \rangle$ space.

Figure 2: Investigation on the impact of BERTweet's fine-tuning for the transfer of class semantics onto the expected $\langle inference, information \rangle$ space in terms of the $[CLS]$ tokens for tweet classification. Considering the classes, (a) highlights the tightening of tweet embeddings towards their respective ideal class poles. Considering the distribution of tweets, (b) emphasizes that each expected quadrant corresponds to the anticipated majority class.

	Inference		Information		Multi-Class	
Model	Frozen	Dynamic	Frozen	Dynamic	Frozen	Dynamic
Closed-Topic (6-fold) Validation						
Length	62.34		71.47		38.26	
RF + TF-IDF	76.12		80.56		55.65	
Vanilla BERTweet	73.12	84.54	66.49	83.55	42.87	71.05
Augmented BERTweet	84.49	**86.68**	79.22	84.57	67.07	73.80
WRAPresentations	**86.88**	86.62	**81.54**	**86.30**	**71.07**	**75.29**
Cross-Topic (6-fold) Validation						
Length	61.99		71.55		38.17	
RF + TF-IDF	73.93		80.16		53.29	
Vanilla BERTweet	70.28	83.15	66.15	82.22	39.00	68.12
Augmented BERTweet	84.20	84.25	79.38	83.31	66.41	69.99
WRAPresentations	**86.83**	**86.27**	**81.54**	**84.90**	**70.93**	**73.54**

Table 4: Macro F1 scores of each classifier for inference and information detection, and all four classes.

Model	Reason		Statement		Notification		None	
	Frozen	Dynamic	Frozen	Dynamic	Frozen	Dynamic	Frozen	Dynamic
Closed-Topic (6-fold) Validation								
Length	61.68		20.19		14.47		56.72	
RF + TF-IDF	69.35		17.30		63.35		72.62	
Vanilla BERTweet	66.05	74.98	00.00	53.99	43.80	77.62	61.63	77.62
Augmented BERTweet	74.50	76.82	49.53	58.37	70.95	**80.28**	73.29	79.71
WRAPresentations	**77.34**	**78.14**	**58.66**	**60.96**	**72.61**	79.36	**75.67**	**82.72**
Cross-Topic (6-fold) Validation								
Length	61.78		19.32		14.49		57.09	
RF + TF-IDF	68.61		13.33		62.75		68.46	
Vanilla BERTweet	63.57	73.15	00.00	47.40	35.79	74.92	56.64	77.01
Augmented BERTweet	75.18	75.10	46.34	51.74	71.61	75.71	72.50	77.42
WRAPresentations	**77.13**	**77.05**	**57.62**	**58.33**	**73.05**	**78.45**	**75.91**	**80.33**

Table 5: F1 scores of the classifiers for identifying the four classes used in inference and information detection.

Further, WRAPresentations clearly improved performance for Statement, the least common and most difficult class to predict when comparing the remaining classifiers. Thereby, all other classifiers perform below or slightly above chance agreement for closed-topic validation and generalization across topics for this class, where Vanilla BERTweet even achieved 00.00% F1 when frozen, showcasing the necessity for adjusting classifiers and embeddings to specific classes, see Table 5.

6 Discussion

WRAPresentations consistently outperforms all models, with the exception of a marginal -0.06% F1 decrease compared to Augmented BERTweet with dynamic representations for task (1) of closed-topic evaluation, while totally excelling across topics.

Augmented BERTweet performs stronger in detecting instances without inference, as demonstrated by the substantial 9.33% F1 increase for the Notification class with dynamic embeddings, see upper half of Table 5. Considering that tasks (1) and (2) are aggregations derived from the results of task (3), WRAPresentations enhances the overall performance of task (3) for achieving the best results, prioritizing an improvement in task (2) while incurring a slight decrease in task (1).

This effect emerges as further refinements for additional classification improvements can partially replace the enriched understanding of inference and information in tweets, exposing unconsidered class features during optimization of the head.

However, examining WRAPresentations' frozen states, superior in closed and cross-topic validation, underscores the advantages of our pre-classification fine-tuning focused on semantic similarity in tweets for enhanced classification strength, see Table 4, 5.

Due to our multi-task fine-tuning approach, BERTweet can employ more robust embeddings for both classification scenarios, showcasing adaptability and generalizability across all three argument mining tasks on Twitter, including challenging instances like identifying the Statement class.

7 Conclusion and Ongoing Work

Our pre-classification multi-task fine-tuning approach considerably improves the specification of embeddings of BERTweet to encode diverse manifestations of inference and information, especially supporting the classification of tweets in TACO.

BERTweet's optimized embeddings, enhanced through contrastively learning semantic similarity, offer improved adaptability to actual class signals and support cross-topic generalization when compared to conventional argument mining on Twitter.

In this regard, we can successfully contribute WRAPresentations, a contrastively optimized embedding model, and the advanced classification model WRAP for inference and information-driven argument mining across diverse topics on Twitter.

We also provide grounds for assuming that the augmentation of tweets constitutes a valuable asset within this domain of research.

Given our results demonstrating successful pre-classification fine-tuning with tweet augmentations and strong performance on original tweets, we pose the broader question of the necessity of using tweets for argument mining on Twitter, exploring whether tweet-like instances from other domains alone are sufficient.

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Limitations

For our work, we report the following limitations:

The field of argument mining on Twitter is subject to Twitter's data regulations, which allow only the publication of tweet identifiers but not their text. This poses challenges to the reproducibility of research and the potential loss of data due to deleted tweets when retrieved via their identifiers through the Twitter API, which provides a limited 1,500 free queries per month. However, for our study, we were able to obtain all preserved tweets from TACO by contacting the authors.

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