A Appendix

Here, we show some additional experiment results and their implications in support of our proposed framework for sentiment prediction.

A.1 Interpretation of node centrality scores and layer influences

In Table 4 and Figure 7 we precisely show three example tweets and their cos witranked centrality scores calculated by our proposed method. The first example is all about a terrorist attack in India and India's Prime Minister Modi's reaction to it. In simple multi-layer view of a tweet, we see *india, pm, modi, speech* - keywords related to how India reacts have more centrality than the attack *#uriattack* and one terrorist named *#burhanwani*. It is interesting to look at the list of nodes selected by our plain and sentiment-infused node expansion methods in Table 4. The list of nodes for expansion related to *#uriattack* talk about the surgical strike, home minister, defence minister, soldiers killed in this attack etc. and have higher ranks. The second tweet is one under-specified tweet where India's Prime Minister greets soldiers. Here, our node expansion methods beautifully guess that this greeting is related to India's success in #surgicalstrike as India's reaction to *#uriattack*. Keywords related to the war, causalities and related emotions like *army, pak, loc, diplomatic, refute, lose, collateral, pray, roar* come higher in centrality-score based ranking. Example 3 is one multilingual tweet whose main theme is *Goods & Services Tax (GST)* (a bill related to tax payment adopted by the Indian government in 2017). Although the original tweet mentions @*narendramodi* PM of India and uses Hindi keywords, but the nodes selected for expansion rightfully capture about finance ministry (@*arunjaitley,* @*finminindia*), home ministry (@*amitshah*), economic transformation and mostly positive sentiments about it. Also, as we create one large multi-layer heterogeneous network from the tweet corpus to train node embedding methods, the layer influence calculated by our method ranks hashtag layer higher than mention layer followed by keyword layer ($H > M > K$). This ranking is pretty intuitive as we have most of the influential nodes in the hashtag (trending topics) and mention (Twitter handles of important personalities) networks. Whereas, the keyword layer has a large number of keywords, among them, the entire population of the less frequently used keywords bring down the overall influence score of this layer.

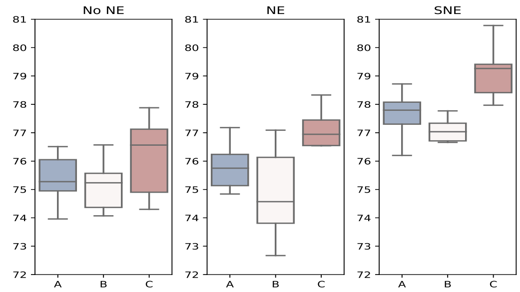


Figure 5: Effectiveness of centrality score-based biased representation of tweets A:Unbiased, B:Node2Vec, C:Biased representation of networked-tweets for No Node Expansion(No NE), Node Expansion(NE), sentiment polarized node expansion (SNE) methods. Accuracy(%) of sentiment prediction in Y-axis.

A.2 Novelty of centrality score-based biasing

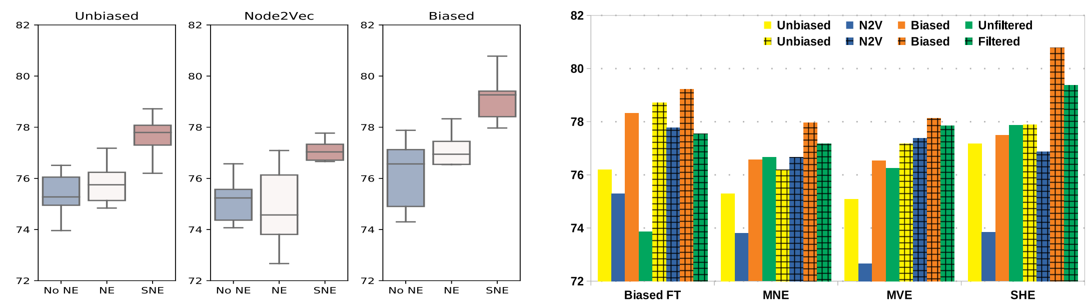
We created boxplots of aggregated performances of three competing methods (unbiased, Node2Vec and biased as in Table 3) for tweet network representation and generation of RW sequences. From Figure 5, for each networked view of tweets (NE, No NE, SNE), it is evident that our centrality-score based RW sequences are better than unbiased and Node2Vec biasing based RW sequences. Plain BFS, DFS exploration-based Node2Vec biasing does not seem to be intuitive for tweet sentiment classification. Our node & layer importance based biased RW sequences beat Node2Vec by 3.1% and unbiased RWs by 1.7% on average.

A.3 Novelty of (sentiment polarized) node expansion

In Figure 6(a), as we create boxplots of aggregated performances of three competing methods for networked tweet representations, namely, multi-layer tweet network with no node expansion (No NE), with plain node expansion (NE) and with sentiment polarized node expansion (SNE) as in Table 3) for different RW algorithms (A:unbiased, B:Node2Vec, C:biased) across various embedding methods, each node expansion method beats the plain view without any node expansion. Precisely, NE beats No NE by 1.38%, SNE beats NE by 9.19% and SNE beats No NE by a huge margin of 10.57% on average. We can conclude that plain NE, that is, extending networked-view of a tweet by including a few similar, central nodes, serves our purpose decently. And this decent performance is enhanced by SNE by a huge margin. Another two aspects, also beautifully

Tweet	New nodes for expansion	sentiment polarized nodes
T1	#pakistanarmy, @amitshah, @rajnathsingh, @finminindia, @pmoindia, ji, pls, request, indiansoldiers, takesover, frmindia, pakintensifies, brave, aftrstrikes, surgstrikes, soldiers, killed	@pmoindia, @amitshah, @finminindia, request, takesover, aftrstrikes, indiansoldiers, pakintensifies, frmindia, soldiers, killed
T2	#surgicalstrike, #surgical, #surgicalstrikes, @saikatd, initiative, detailed, nomura, indian, clai, outstrip, lic, operational, offenders, collateral, initiative, lose, pakistani, roar, claims, pray, remembered, diplomatic, write, refute, army, indian, pak, loc	#surgicalstrikes, offenders, collateral, pray, remembered, diplomatic, roar, write, pak, army, pakistan
T3	#gstbill, #gst, @arunjaitley, @finminindia, @adhia, @amitshah, @pmoindia, transformation, congratulation, request, cgstate, lagu, ke, wishes, nahi, hind, liye, didi, pls, ji, taxation, finance	@pmoindia, @amitshah, @arunjaitley, @finminindia, didi, nahi, request, cgstate, transformation, congratulation

Table 4: Nodes selected for tweet view expansion. **Tweet 1:** *@asadmunir38 Modi is agressive since #UriAttack, #BurhanWani & PM speech @UNGAPak needs to start dialogue with neighbours India, Afghan*; **Tweet 2:** *@narendramodi #GreetingsToSoldiers*; **Tweet 3:** *@narendramodi Thank you Sir GST laagu karne ke liye is India great*



(a) (b)

Figure 6: Effectiveness of (sentiment polarized) node expansion in tweet-networks. `Figure a`: A:Unbiased, B:Node2Vec, C:Biased representation of networked-tweets for No Node Expansion(No NE), Node Expansion(NE), sentiment polarized node expansion (SNE) methods. Accuracy(%) of sentiment prediction in Y-axis. `Figure b`: Patterned and plain colored bars shows the performance with and without sentiment polarized node expansion respectively.

captured by Figures: [5, 6(a)] are – i) boxes pertaining to SNE methods have low variance reflecting that it is pretty stable, reliable method to enhance tweet network view, ii) any kind of expanded tweet view always makes the performance of centrality based biasing algorithm more reliable.

In Figure 6(b) we compare two node expansion methods that we propose as part of our framework. Evidently, SNE offers a performance improvement of 8.4% over plain NE on average across all four embedding methods. Even SNE improves the tweet representation with a list of unfiltered nodes without any network structure by an accuracy improvement of 1.8% on average – which clearly shows that list of nodes selected for sentiment polarized expansion are less-noisy and informative in the context of tweet sentiment prediction.

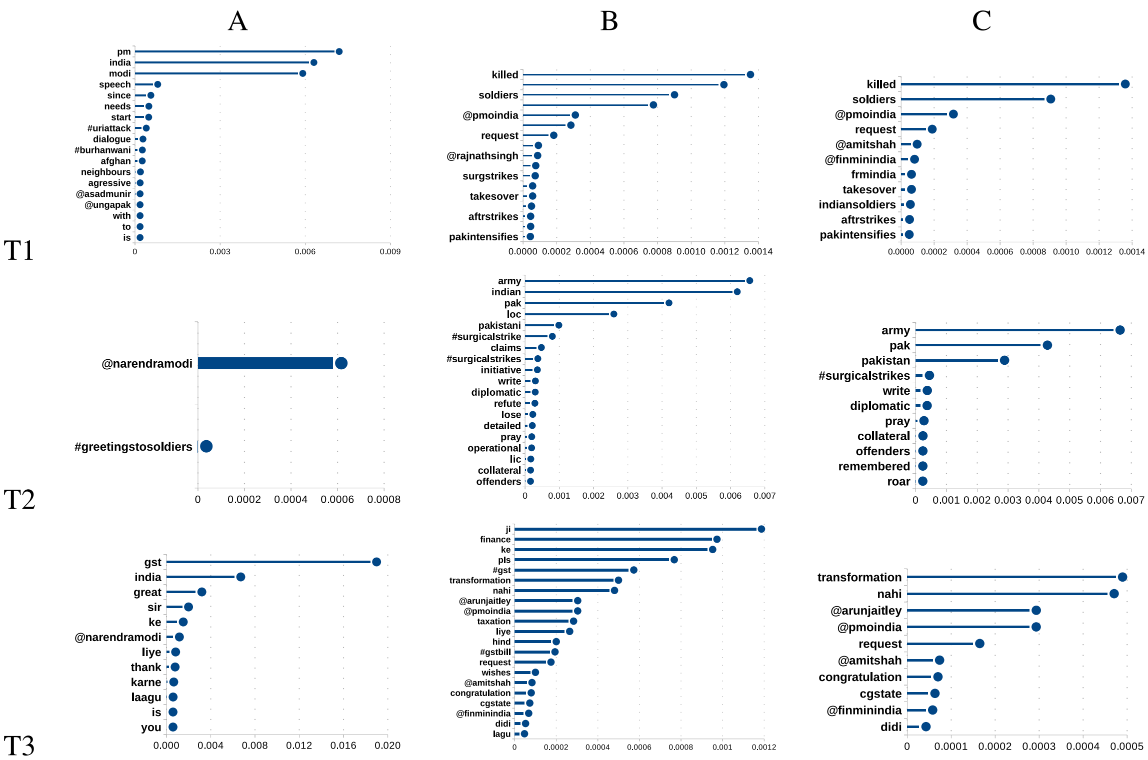


Figure 7: Tweet component centrality rankings A: without node expansion, B: plain node expansion, C: sentiment polarized node expansion. **T1**:*@asadmunir38 Modi is agressive since #UriAttack, #BurhanWani & PM speech @UNGAPak needs to start dialogue with neighbours India, Afghan*; **T2***@narendramodi #GreetingsToSoldiers*; **T3***@narendramodi Thank you Sir GST laagu karne ke liye is India great*.