Modeling Post-level Sentiment Evolution in Online Forum Threads

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Keywords: Opinion Propagation, Post-Level Sentiment Analysis, Graph Theory, Forum Threads.

Abstract: Opinion propagation analysis in online forum threads is a relatively new research field emerging in the context of the increasing popularity of forums. Many changes occur over time in online forum threads since new users intervene in the discussion and express their opinions. In this paper, we propose a novel task in the analysis of opinion propagation in online forum threads, i.e. the modeling of post-level sentiment evolution in online forum threads. This task consists in the analysis of post-level sentiment evolution in an online forum thread in order to obtain a simplified model of this evolution. Based on opinion mining, graph theory, and post-level sentiment analysis, our method comprises five steps: removal of posts containing only facts, post-level sentiment identification, removal of posts with neutral sentiment, aggregation of parent-child vertices, and aggregation of sibling vertices. We evaluate the proposed method on real-world forum threads, and the results of our experiments are presented in the visualization interfaces.

1 INTRODUCTION

Contemporary societies are experiencing the prominent phenomenon of online interaction through social media, which has huge implications for both individuals and companies. The propagation of opinions in social media is a dynamic phenomenon involving a considerable number of people who establish or end different types of relationships between them and also produce vast quantities of data by giving or changing their opinions. The propagation of opinions has significantly different characteristics compared to all previous periods: it is rapid, less costly, and therefore more widespread than ever.

Several studies have addressed opinion propagation in social media. Ku et al. (Ku et al., 2006) analyzed the opinion tracking in a news corpus for four candidates during Taiwan's 2000 presidential election. Recently, a method for studying the problem of opinion propagation in online forum threads has been proposed at user level (Cercel and Trausan-Matu, 2014c). For more details about the analysis of opinion propagation in online social networks, see (Cercel and Trausan-Matu, 2014b).

Being a type of social media, a forum thread can be modeled as a post-reply graph, where vertices are posts, and edges are replies between posts. The post-reply graph associated with an online forum thread is increasing by adding both new vertices and edges as new posts appear over time. In this paper we address the modeling of post-level sentiment evolution in online forum threads as a new task of opinion propagation analysis in online forum threads.

2 THE ARCHITECTURE OF THE PROPOSED METHOD

We divided our method for the post-level sentiment evolution task in an online forum thread into the following steps:

- Preprocessing of each post in the initial post-reply graph at time step t_τ, $\tau \in \mathbb{N}^*$. The initial post-reply graph at time step t_τ, $\tau \in \mathbb{N}^*$, is denoted by $G^0_{DT}(t_\tau)(V^0_{DT}(t_\tau), E^0_{DT}(t_\tau))$.
- Filtration of the post-reply graph $G^0_{DT}(t_\tau)(V^0_{DT}(t_\tau), E^0_{DT}(t_\tau))$ in order to remove the posts that contain only facts and do not contain opinions about the subject of the forum thread. The post-reply graph obtained at the end of this step is denoted by $G^1_{DT}(t_\tau)(V^1_{DT}(t_\tau), E^1_{DT}(t_\tau))$.
- Identification of the sentiment of each post from

Cercel D. and Trausan-Matu S..
Modeling Post-level Sentiment Evolution in Online Forum Threads.
DOI: 10.5220/0005286605880593
In *Proceedings of the International Conference on Agents and Artificial Intelligence* (ICAART-2015), pages 588-593
ISBN: 978-989-758-074-1

the previously filtered graph $G^1_{DT}(t_\tau)(V^1_{DT}(t_\tau), E^1_{DT}(t_\tau))$.

- Filtration of the post-reply graph $G^1_{DT}(t_\tau)(V^1_{DT}(t_\tau), E^1_{DT}(t_\tau))$ in order to remove the posts with neutral sentiment. The post-reply graph obtained at the end of this step is denoted by $G^2_{DT}(t_\tau)(V^2_{DT}(t_\tau), E^2_{DT}(t_\tau))$.
- Aggregation of the parent-child vertices from the previously filtered graph $G^2_{DT}(t_\tau)(V^2_{DT}(t_\tau), E^2_{DT}(t_\tau))$. The multipost-reply graph obtained at the end of this step is denoted by $G^3_{DT}(t_\tau)(V^3_{DT}(t_\tau), E^3_{DT}(t_\tau))$.
- Aggregation of the sibling vertices from the previously aggregated graph $G^3_{DT}(t_\tau)(V^3_{DT}(t_\tau), E^3_{DT}(t_\tau))$. The aggregated multipost-reply graph obtained at the end of this step is denoted by $G^4_{DT}(t_\tau)(V^4_{DT}(t_\tau), E^4_{DT}(t_\tau))$.

In the preprocessing step, we apply specific techniques of natural language processing such as tokenization, part-of-speech tagging, syntactic parsing, and coreference resolution (Manning and Schütze, 1999) to each post in the post-reply graph $G^0_{DT}(t_\tau)$ $(V^0_{DT}(t_\tau), E^0_{DT}(t_\tau))$. In the next subsections, we describe the remaining step of the method proposed by us for the post-level sentiment evolution task.

2.1 Removing Posts That Contain Only Facts

In this step, we remove the vertices that do not contain opinions about the subject of the forum thread. The other vertices of the post-reply graph $G^0_{DT}(t_\tau)(V^0_{DT}(t_\tau), E^0_{DT}(t_\tau))$ will not be changed. The outline of the algorithm for this step is given in Algorithm 1. We perform the initialization of the post-reply graph $G^1_{DT}(t_\tau)(V^1_{DT}(t_\tau), E^1_{DT}(t_\tau))$ by using the post-reply graph $G^0_{DT}(t_\tau)(V^0_{DT}(t_\tau), E^0_{DT}(t_\tau))$ (A1 : 1-2). Then, we apply the Breadth First Search algorithm (Cormen et al., 2009) from the root vertex v_1 and save its output in a list (A1 : 3).

For each current vertex in the list, different from the root vertex v_1, we follow the next steps. First, we obtain pairs in the form of *(noun term, opinion word)* from the current vertex, where the *noun term* is semantically related to a word that appears in the subject of the forum thread (A1 : 8) For more details about this substep, see (Cercel and Trausan-Matu, 2014c). If there are no pairs *(noun term, opinion word)* in the current vertex, we eliminate this vertex (A1 : 9-17). To this end, we obtain the parent vertex of the current vertex (A1 : 10). As regards each child vertex of the current vertex, we create an edge between each child vertex and the current vertex's parent vertex (A1 : 14). Finally, we eliminate the current vertex from the set $V^1_{DT}(t_\tau)$ (A1 : 15).

Algorithm 1 (A1): Removing Posts that Contain only Facts

```
Input: G⁰DT(tτ)(V⁰DT(tτ), E⁰DT(tτ))
Output: G¹DT(tτ)(V¹DT(tτ), E¹DT(tτ))
 1:  V¹DT(tτ) ← V⁰DT(tτ)
 2:  E¹DT(tτ) ← E⁰DT(tτ)
 3:  M ← BreadthFirstSearch(v1)
 4:  for each node crtNode in M do
 5:      if crtNode = v1 then
 6:          continue
 7:      endif
 8:      Ω ← FilteringDependencyRelationsfromPost(crtNode)
 9:      if Ω = ∅ then
10:          parentNode ← GetParentNode(crtNode)
11:          N ← GetChildrenNodes(crtNode)
12:          for each node childNode in N do
13:              E¹DT(tτ) ← E¹DT(tτ) \ (childNode, crtNode)
14:              E¹DT(tτ) ← E¹DT(tτ) ∪ (childNode, parentNode)
15:              V¹DT(tτ) ← V¹DT(tτ) \ {crtNode}
16:          end for
17:      endif
18:  endfor
```

2.2 Post-level Sentiment Identification

We determine the sentiment of a post by taking into account the sentiment strength of the opinion words from this post. Let $p \in P_{DT}(t_\tau)$ be a post in the forum thread. The sentiment score for the post p is given by the following formula:

$$sentimentScore(p) = \frac{\sum_{i=1 \wedge w \in S_J^i \wedge w \in S_R^i}^{4} score(w)\lambda_i}{\sum_{i=1}^{4} |S_J^i| + \sum_{i=1}^{4} |S_R^i| + |S_V|} + \frac{\sum_{w \in S_V} score(w)\lambda_4}{\sum_{i=1}^{4} |S_J^i| + \sum_{i=1}^{4} |S_R^i| + |S_V|} \quad (1)$$

where: *score(w)* is the sentiment score for the opinion word w; S^1_J is the set of superlative adjectives; S^2_J is the set of comparative adjectives of superiority; S^3_J is the set of comparative adjectives of inferiority; S^4_J is the set of adjectives of other degree; S^1_R is the set of superlative adverbs; S^2_R is the set of comparative adverbs of superiority; S^3_R is the set of comparative adverbs of inferiority; S^4_R is the set of adverbs of other degree; S_V is the set of verbs; $|S|$ denotes the power set of S.

To identify the sentiment score of an opinion word, we used SentiWordNet (Baccianella and Sebastiani, 2010). The corresponding algorithm is described in (Cercel and Trausan-Matu, 2014a). The variables $\lambda_1, \lambda_2, \lambda_3$, and λ_4 take the values 0.9, 0.6, -0.6, and 0.3, respectively. The post $p \in P_{DT}(t_\tau)$ is considered to express a positive sentiment if $sentimentScore(p) \in (0, 1]$, a negative sentiment if *sentimentScore(p)* $\in$ *[-1, 0)*, or a neutral sentiment if *sentimentScore(p) = 0*.

2.3 Removing Posts with Neutral Sentiment

In this step, the removed vertices do not contain opinions with positive or negative sentiments about the subject of the forum thread, but only opinions with neutral sentiment. The outline of this algorithm is given in Algorithm 2. We apply the Breadth First Search algorithm from the root vertex v_l and save its output in a list (A2 : 3). For each current vertex in the list, different from the root vertex v_l, we follow the next steps. First, we calculate the sentiment score of the current vertex by using Formula 1 (A2 : 8). If this sentiment score is non-zero, we obtain the parent vertex of the current vertex (A2 : 10) and create an edge between the current vertex's each child vertex and the current vertex's parent vertex (A2 : 14). Finally, we eliminate the current vertex from the set $V^2_{DT}(t_\tau)$ (A2 : 15).

Algorithm 2 (A2): Removing Posts with Neutral Sentiment

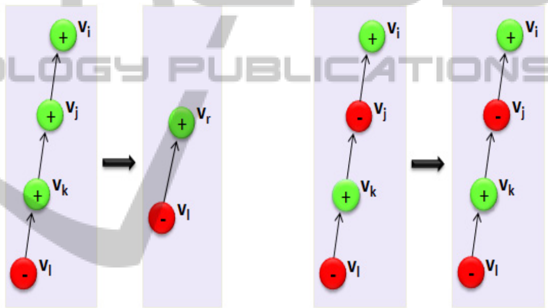
Input: $G^1_{DT}(t_\tau)(V^1_{DT}(t_\tau), E^1_{DT}(t_\tau))$
Output: $G^2_{DT}(t_\tau)(V^2_{DT}(t_\tau), E^2_{DT}(t_\tau))$
1: $V^2_{DT}(t_\tau) \leftarrow V^1_{DT}(t_\tau)$
2: $E^2_{DT}(t_\tau) \leftarrow E^1_{DT}(t_\tau)$
3: M $\leftarrow$ BreadthFirstSearch(v_l)
4: **for each** node crtNode in M **do**
5:   **if** crtNode = v_l **then**
6:     **continue**
7:   **endif**
8:   crtNodeScore $\leftarrow$ sentimentScore(crtNode)
9:   **if** crtNodeScore = 0 **then**
10:     parentNode $\leftarrow$ GetParentNode(crtNode)
11:     N $\leftarrow$ GetChildrenNodes(crtNode)
12:     **for each** node childNode in N **do**
13:       $E^1_{DT}(t_\tau) \leftarrow E^2_{DT}(t_\tau) \setminus$ (childNode, crtNode)
14:       $E^2_{DT}(t_\tau) \leftarrow E^2_{DT}(t_\tau) \cup$ (childNode, parentNode)
15:       $V^2_{DT}(t_\tau) \leftarrow V^2_{DT}(t_\tau) \setminus$ {crtNode}
16:     **end for**
17:   **endif**
18: **endfor**

2.4 Aggregation of Parent-Child Vertices

The aggregation of parent-child vertices occurs according to the following definition:

Definition 1 (Aggregation of Parent-Child Vertices). *Given at time step* t_τ, $\tau \in \mathbb{N}^*$, *the forum thread* (T_{DT}, S_{DT}, $U_{DT}(t_\tau)$, $P_{DT}(t_\tau)$, $R_{DT}(t_\tau)$) *from an online forum and its corresponding post-reply graph* $G^2_{DT}(t_\tau)(V^2_{DT}(t_\tau), E^2_{DT}(t_\tau))$, *then two vertices* $v_i, v_k \in V^2_{DT}(t_\tau)$, $v_i = (v_i^p, v_i^u, v_i^{tm}, v_i^{op})$, $v_k = (v_k^p, v_k^u, v_k^{tm}, v_k^{op})$, $(v_i, v_k) \in E^2_{DT}(t_\tau)$ *will be merged if these two vertices* $v_i, v_k \in V^2_{DT}(t_\tau)$ *have the same sentiment (positive or negative). The result of the aggregation of the vertices* $v_i, v_k \in V^2_{DT}(t_\tau)$ *is a single vertex* $v_r = (v_r^p, v_r^u, v_r^{tm}, v_r^{op}) \in V^2_{DT}(t_\tau)$ *characterized by:* $v_r^p = v_i^p \cup v_k^p$, $v_r^u = v_i^u \cup v_k^u$, $v_r^{tm} = v_i^{tm} \cup v_k^{tm}$, *and* $v_r^{op} = v_i^{op} \cup v_k^{op}$.

Let us consider an example for illustrating this definition. In Figure 1(a), the vertex v_l is a reply to the vertex v_k, the vertex v_k is a reply to the vertex v_j, and the vertex v_j is a reply to the vertex v_i. The vertices v_i, v_j and v_k have the same positive sentiment and will be aggregated according to Definition 1. The result is the vertex v_r with positive sentiment. The vertex v_l is a reply to the vertex v_r. In contrast, in Figure 1(b), on the path from the vertex v_l to the vertex v_i there is an alternation between vertices with positive and negative sentiments. Therefore, Definition 1 cannot be applied to this second example.



(a) (b)

Figure 1: (a) Example of aggregation of parent-child vertices; (b) Example of a non-possible aggregation of parent-child vertices.

The outline of the algorithm that transforms the post-reply graph $G^2_{DT}(t_\tau)(V^2_{DT}(t_\tau), E^2_{DT}(t_\tau))$ into the post-reply graph $G^3_{DT}(t_\tau)(V^3_{DT}(t_\tau), E^3_{DT}(t_\tau))$ is given in Algorithm 3. We apply the Breadth First Search algorithm from the root vertex v_l and save its output in a list (A3 : 3). For each current vertex in the list, we obtain its parent vertex (A3 : 5).

If the current vertex in the list is different from the root vertex v_l or the current vertex's parent vertex is different from the root vertex v_l, we follow the next steps (A3 : 6-8). First, we calculate the sentiment score for the current vertex and its parent vertex by using Formula 1 (A3 : 9-10). If the current vertex and its parent vertex have the same sentiment (negative or positive), we obtain the child vertices of the current vertex (A3 : 12). Then, we create an edge between the current vertex's each child and the current vertex's parent vertex (A3 : 15). Moreover, we update the components (the contents of the post(s), the time step(s), the user(s), and the opinions expressed in the post(s)) of the current vertex's parent vertex (A3 : 16). Finally, we eliminate the current vertex from the set $V^3_{DT}(t_\tau)$ (A3 : 17).

Algorithm 3 (A3): Aggregation of Parent-Child Vertices

Input: $G^2_{DT}(t_\tau)(V^2_{DT}(t_\tau), E^2_{DT}(t_\tau))$
Output: $G^3_{DT}(t_\tau)(V^3_{DT}(t_\tau), E^3_{DT}(t_\tau))$
1: $V^3_{DT}(t_\tau) \leftarrow V^2_{DT}(t_\tau)$
2: $E^3_{DT}(t_\tau) \leftarrow E^2_{DT}(t_\tau)$
3: M ← BreadthFirstSearch(v_1)
4: **for each** node crtNode in M **do**
5: parentNode ← GetParentNode(crtNode)
6: **if** crtNode = v_1 or parentNode = v_1 **then**
7: **continue**
8: **end if**
9: crtNodeScore ← sentimentScore (crtNode)
10: parentNodeScore ← sentimentScore (parentNode)
11: **if** crtNodeScore * parentNodeScore > 0 **then**
12: N ← GetChildrenNodes(crtNode)
13: **for each** node childNode in N **do**
14: $E^3_{DT}(t_\tau) \leftarrow E^3_{DT}(t_\tau) \setminus$ (childNode, crtNode)
15: $E^3_{DT}(t_\tau) \leftarrow E^3_{DT}(t_\tau) \cup$ (childNode, parentNode)
16: InformationUpdate(parentNode, crtNode)
17: $V^3_{DT}(t_\tau) \leftarrow V^3_{DT}(t_\tau) \setminus$ {crtNode}
18: **end for**
19: **end if**
20: **end for**

2.5 Aggregation of Sibling Vertices

The aggregation of sibling vertices occurs according to the following definition:

Definition 2 (Aggregation of Sibling Vertices). *Given at time step t_τ, $\tau \in \mathbb{N}^*$, the forum thread (T_{DT}, S_{DT}, $U_{DT}(t_\tau)$, $P_{DT}(t_\tau)$, $R_{DT}(t_\tau)$) from an online forum and its corresponding graph $G^3_{DT}(t_\tau)(V^3_{DT}(t_\tau), E^3_{DT}(t_\tau))$, then two vertices v_i, $v_k \in V^3_{DT}(t_\tau)$, $v_i = (v_i^p, v_i^u, v_i^{tm}, v_i^{op})$, $v_k = (v_k^p, v_k^u, v_k^{tm}, v_k^{op})$, will be merged if there is $v_j \in V^3_{DT}(t_\tau)$ so that $(v_i, v_j) \in E^3_{DT}(t_\tau)$, $(v_k, v_j) \in E^3_{DT}(t_\tau)$, and the vertices v_i, $v_k \in V^3_{DT}(t_\tau)$ have the same sentiment (positive or negative). The aggregation result of the sibling vertices v_i, $v_k \in V^3_{DT}(t_\tau)$ is a single vertex $v_r = (v_r^p, v_r^u, v_r^{tm}, v_r^{op}) \in V^4_{DT}(t_\tau)$ characterized by $v_r^p = v_i^p \cup v_k^p$, $v_r^u = v_i^u \cup v_k^u$, $v_r^{tm} = v_i^{tm} \cup v_k^{tm}$, and $v_r^{op} = v_i^{op} \cup v_k^{op}$.*

Let us consider an example for illustrating this definition. In Figure 2, the vertex v_l is a reply to the vertex v_j, and the vertex v_j is a reply to the vertex v_i. Both vertices v_i and v_k have the same sentiment, and their parent vertex v_s is common. Applying the definition of the aggregation of sibling vertices for the two vertices v_i and v_k, we obtain the vertex v_r of positive sentiment, where the vertex v_r is a reply to the vertex v_s.

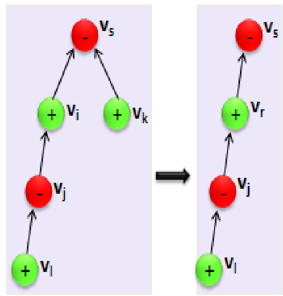


Figure 2: Example of aggregation of sibling vertices.

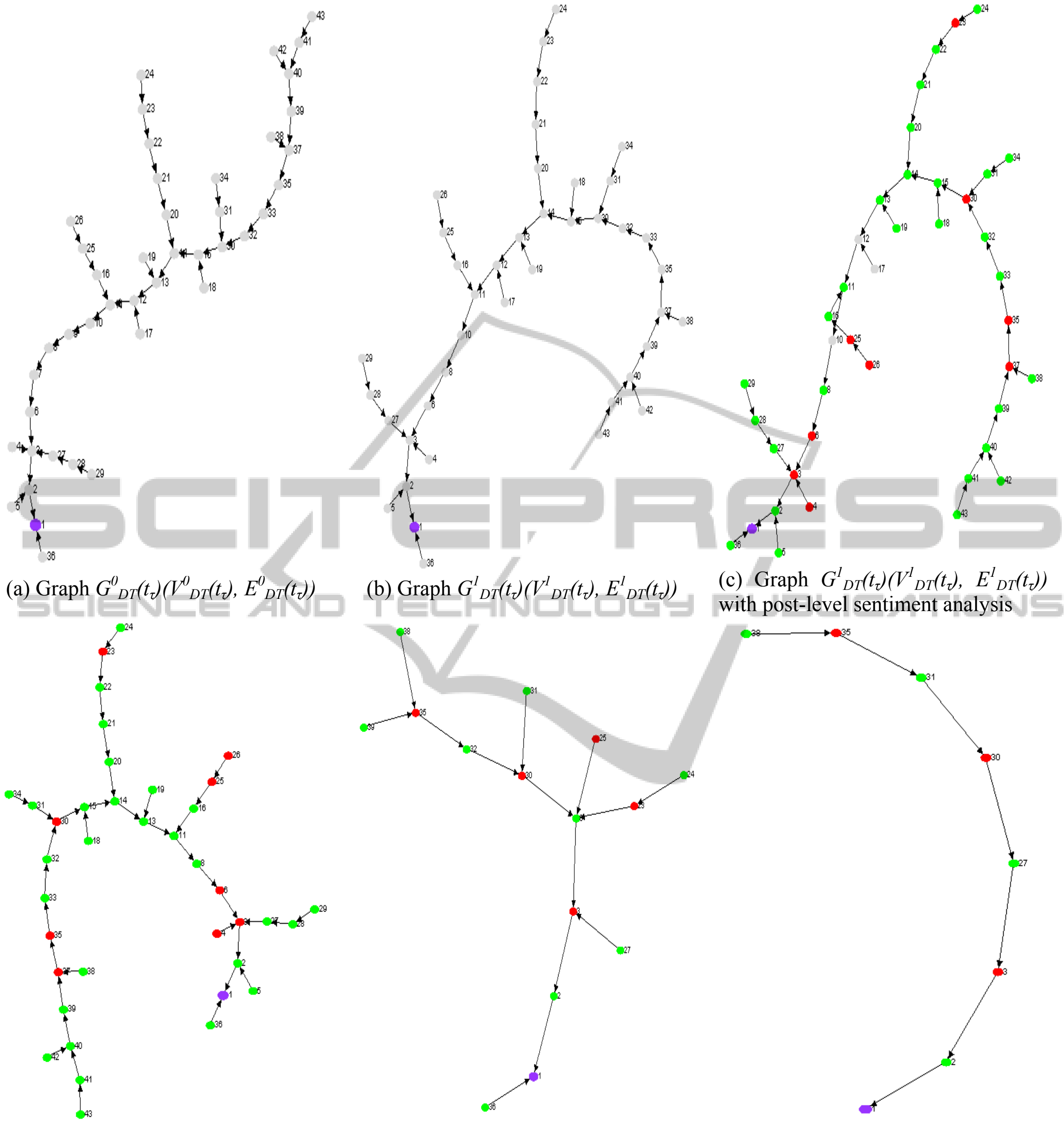
The outline of the algorithm that transforms the graph $G^3_{DT}(t_\tau)(V^3_{DT}(t_\tau), E^3_{DT}(t_\tau))$ into the graph $G^4_{DT}(t_\tau)(V^4_{DT}(t_\tau), E^4_{DT}(t_\tau))$ is given in Algorithm 4.

Algorithm 4 (A4): Aggregation of Sibling Vertices

Input: $G^3_{DT}(t_\tau)(V^3_{DT}(t_\tau), E^3_{DT}(t_\tau))$
Output: $G^4_{DT}(t_\tau)(V^4_{DT}(t_\tau), E^4_{DT}(t_\tau))$
$V^4_{DT}(t_\tau) \leftarrow V^3_{DT}(t_\tau)$
$E^4_{DT}(t_\tau) \leftarrow E^3_{DT}(t_\tau)$
M ← {v_1}
while M != ∅
positiveNodesList ← ∅
negativeNodesList ← ∅
crtNode ← RemoveNode(M)
N ← GetChildrenNodes(crtNode)
for each node childNode in N **do**
childNodeScore ← sentimentScore(childNode)
if childNodeScore > 0 **then**
if positiveNodesList = ∅ **then**
positiveNode ← childNode
else
positiveNode ← positiveNode ∪ {childNode}
$V^4_{DT}(t_\tau) \leftarrow V^4_{DT}(t_\tau) \setminus$ {crtNode}
end if
end if
if childNodeScore < 0 **then**
if negativeNode = ∅ **then**
negativeNode ← childNode
else
negativeNode ← negativeNode ∪ {childNode}
$V^4_{DT}(t_\tau) \leftarrow V^4_{DT}(t_\tau) \setminus$ {crtNode}
end if
end if
end for
if positiveNodesList != ∅ **then**
for each node childNode in positiveNodesList **do**
AddNode(M, childNode)
end for
end if
if negativeNodesList != ∅ **then**
for each node childNode in negativeNodesList **do**
AddNode(M, childNode)
end for
end if
end while

We can define the aggregated multipost-reply graph $G^4_{DT}(t_\tau)(V^4_{DT}(t_\tau), E^4_{DT}(t_\tau))$, as follows:

Definition 3 (Aggregated Multipost-Reply Graph). *Given at time step t_τ, $\tau \in \mathbb{N}^*$, a forum thread*



(a) Graph $G^0{}_{DT}(t_\tau)(V^0{}_{DT}(t_\tau), E^0{}_{DT}(t_\tau))$ (b) Graph $G^1{}_{DT}(t_\tau)(V^1{}_{DT}(t_\tau), E^1{}_{DT}(t_\tau))$ (c) Graph $G^1{}_{DT}(t_\tau)(V^1{}_{DT}(t_\tau), E^1{}_{DT}(t_\tau))$ with post-level sentiment analysis

(d) Graph $G^2{}_{DT}(t_\tau)(V^2{}_{DT}(t_\tau), E^2{}_{DT}(t_\tau))$ (e) Graph $G^3{}_{DT}(t_\tau)(V^3{}_{DT}(t_\tau), E^3{}_{DT}(t_\tau))$ (f) Graph $G^4{}_{DT}(t_\tau)(V^4{}_{DT}(t_\tau), E^4{}_{DT}(t_\tau))$

Figure 3: Modeling of post-level sentiment evolution in the forum thread at time step $t_\tau = t_{43}$.

$(T_{DT}, S_{DT}, U_{DT}(t_\tau), P_{DT}(t_\tau), R_{DT}(t_\tau))$ from an online forum and its corresponding graph $G^3{}_{DT}(t_\tau)(V^3{}_{DT}(t_\tau), E^3{}_{DT}(t_\tau))$ obtained according to Algorithm 3, then the forum thread is associated with an oriented graph $G^4{}_{DT}(t_\tau)(V^4{}_{DT}(t_\tau), E^4{}_{DT}(t_\tau))$ by applying Algorithm 4, where:

- *$V^4{}_{DT}(t_\tau) = \{v''_j \mid v''_j = (\cup v_l^p, \cup v_l^u, \cup v_l^{tm}, \cup v_l^{op}), v_l^p \in P_{DT}(t_\tau), v_l^u \in U_{DT}(t_\tau), v_l^{tm} \in \mathbb{N}, v_l^{op} \subset OS^d{}_{DT}\}$ is the set of vertices in the graph $G^4{}_{DT}(t_\tau)$ so that, if $v''_i, v''_j, v''_k \in V^4{}_{DT}(t_\tau)$, $(v''_i, v''_k) \in E^4{}_{DT}(t_\tau)$, and $(v''_j, v''_k) \in E^4{}_{DT}(t_\tau)$, the vertices v''_i and v''_j have opposite polarities (v''_i has a positive sentiment, and v''_j has a negative sentiment, and vice versa). A vertex v''_j in the set $V^4{}_{DT}(t_\tau)$ is a set of posts $\cup v_l^p$ written by a set of users $\cup v_l^u$ at time steps $\cup v_l^{tm}$.*
- *$E^4{}_{DT}(t_\tau) = \{e''_1, e''_2, ..., e''_s\}$ is the set of edges in the graph $G^4{}_{DT}(t_\tau)$ so that, if $e' = (v''_i, v''_j) \in$*

$E^4_{DT}(t_\tau)$, the set of posts corresponding to the vertex v''_i is a reply to the set of posts corresponding to the vertex v''_j, and the vertices v''_i and v''_j have opposite polarities.

3 EXPERIMENTAL RESULTS

In this section, we present an example of applying the proposed method on a real-world forum thread. More concretely, we perform experiments on a forum thread selected from the Internet Argument Corpus (Walker et al., 2012). This forum thread has the subject "What is God?" and comprises 43 posts (i.e. $t_\tau = t_{43}$). The corresponding post-reply graph $G^0_{DT}(t_{43})$ at time step t_{43} is represented in Figure 3(a).

In Figure 3, the vertices in the graphs are represented by certain colors: the root vertex by the purple color, the vertices with positive sentiment by the green color, the vertices with negative sentiment by the red color, and the vertices with neutral sentiment by the gray color. Figure 3(b) shows the experimental results for the post-reply graph $G^0_{DT}(t_{43})(V^0_{DT}(t_{43}), E^0_{DT}(t_{43}))$ after removing the posts that contain only facts. All the vertices in the resulted graph $G^1_{DT}(t_{43})(V^1_{DT}(t_{43}), E^1_{DT}(t_{43}))$ contain opinions about the subject of the forum thread.

In Figure 3(c), we represent the sentiment of each post in the post-reply graph $G^1_{DT}(t_{43})(V^1_{DT}(t_{43}), E^1_{DT}(t_{43}))$ identified in the previous step. Figure 3(d) shows the experimental results at the end of the step of filtrating the post-reply graph $G^1_{DT}(t_{43})(V^1_{DT}(t_{43}), E^1_{DT}(t_{43}))$ to remove the posts with neutral sentiment.

Figure 3(e) shows the experimental results after applying the step of aggregating the parent-child vertices in the post-reply graph $G^2_{DT}(t_{43})(V^2_{DT}(t_{43}), E^2_{DT}(t_{43}))$. Figure 3(f) shows the experimental results after applying the step of aggregating the sibling vertices in the multipost-reply graph $G^3_{DT}(t_{43})(V^3_{DT}(t_{43}), E^3_{DT}(t_{43}))$ obtained in the previous step.

4 CONCLUSIONS

In this paper, we address the task of modeling post-level sentiment evolution in online forum threads. Our method has five steps. The successive application of these steps to the initial post-reply graph $G^0_{DT}(t_\tau)$ $(V^0_{DT}(t_\tau), E^0_{DT}(t_\tau))$ will generate a series of intermediate graphs. The aggregated multipost-reply graph $G^4_{DT}(t_\tau)(V^4_{DT}(t_\tau), E^4_{DT}(t_\tau))$ is used to visualize in a simplified way the post-level evolution of sentiments in the initial post-reply graph $G^0_{DT}(t_\tau)$ $(V^0_{DT}(t_\tau), E^0_{DT}(t_\tau))$ at time step t_τ, $\tau \in \mathbb{N}^*$. In the future, our research on opinion propagation will continue in other types of social media than online forum threads.

ACKNOWLEDGEMENTS

This research has been partially supported by the FP7 ICT STREP project LTfLL (http://www.ltfll-project.org/).

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