

# ANALYSIS OF DISCUSSIONS IN TWITTER WITH AN ARGUMENTATION TOOL

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## INTRODUCTION

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What are the main **accepted and rejected** opinions in different domains by Twitter users ?

Are there topics that produce a big **controversy** between Twitter users ?

How **hard** is people **defending** their opinions ? (How important is for them to defend their ideas?)

We consider the use of argumentation based reasoning to help answering such questions

As a first approach, we have considered modelling Twitter discussions as Weighted Labelled Graphs (Weighted Labelled Discussion Graphs)

## Tweets as arguments

Every tweet is a single (atomic) argument

## Social support as weights

We model the social support to a given tweet (opinion) with the weight associated with it

## Relations between tweets as edge labels

We model the possible semantic relation between an answer tweet and a source tweet as an edge label

## DEFINITIONS

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The *Weighted Labeled Discussion Graph* (WLDiSG) for a set of tweets  $T$  is a tuple  $\langle T, E, L, W_R \rangle$ , where:

- $(T, E)$  is a directed graph of tweets such that  $(t_1, t_2) \in E$  if  $t_1$  answers (replies or mentions) tweet  $t_2$
- $L$  is a labelling function

$$L : E \rightarrow \{\textit{criticizes}, \textit{supports}, \textit{none}\}$$

for edges  $(t_1, t_2)$  in  $E$

- $W_R : T \rightarrow R$  assigns a weight value in an ordered set  $R$  to each tweet in  $T$ , representing (a measure of) the social support of the tweet

As a first approach to measure social support for a tweet, we have considered three different sources of information obtained from the tweet:

- **Followers count:** Use the followers count for author of the tweet as measure of support for the tweet (it can be over-estimating the real support)
- **Retweets count:** Use the retweets count for the tweet. Again, not all the retweets are made by people supporting the tweet (it can also over-estimate)
- **Favorites count:** Use the favorite count for the tweet

Interestingly, the retweets and favorite count tend to be positively correlated



Another approach is to aggregate the support of all the tweets  $t_1, t_2, \dots, t_n$  that support a given tweet  $t$  with a non decreasing aggregation operator  $\sqcup : R \times R \rightarrow R$ :

$$W_R^*(t) = \begin{cases} W_R(t), & \text{if } \text{support}(t) = \emptyset \\ (W_R(t) \sqcup W_R(t_1)) \sqcup \dots \sqcup W_R(t_n), & \text{if } \text{support}(t) = \{t_1, \dots, t_n\} \end{cases}$$

We have currently considered two simple aggregation operators:  
max and sum

But we are seeking something between these two extreme functions  
(max seems to under-estimate and sum to over-estimate)

In the work of **E. Cabrio and S. Villata**, Bipolar Argumentation Frameworks were used to derive indirect attacks from support relations in on-line debates

We prefer to use support relations only to increase the relevance (weight) of tweets from its **direct set** of supporters, and not to infer indirect attacks from the input support and attack relations

There is usually very little information in tweets to safely infer indirect attack relations between tweets that are many hops away in a discussion chain

However, we think that in other social networks with more complex arguments extracting more structured arguments is more feasible

# SEMANTICS

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Given a WDisG graph  $G = \langle T, E, L, W_R \rangle$ , the *Valued Argumentation Framework* (VAF) associated with  $G$  is a tuple  $\mathcal{F} = \langle T, attacks, W_R, \geq \rangle$ , where:

$$attacks = \{(t_1, t_2) \mid (t_1, t_2) \in E \text{ and } L(t_1, t_2) = \textit{criticizes}\}$$

and the valued defeat relation:

$$defeats = \{(t_1, t_2) \mid (t_1, t_2) \in attacks \text{ and } (W_R(t_1) \geq W_R(t_2))\}.$$

### Accepted tweets from $G$

It is the solution  $S$  of its associated VAF under **ideal semantics**: the largest admissible conflict-free subset  $S$  such that its defeating tweets in  $T \setminus S$  are not admissible and are defeated by  $S$

## DISCUSSION ANALYSIS TOOL

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1. Discussion Retrieval: takes a root tweet and outputs its WLDiSG
  - 1.1 Obtain plain Discussion Graph
  - 1.2 Label edges (so far we use a SVM-based approach)
  - 1.3 Compute weights
2. Build the Valued AF problem associated with the WLDiSG instance
3. Find the accepted tweets and measure relevant discussion measures

We currently use a generic AF solver for ideal semantics based on the ASPARTIX argumentation framework

When dealing only with acyclic (or bounded tree-width) discussion graphs, we could pick specialized P-time algorithms.

**Future work:** Use the dynPARTIX framework to solve the instances more efficiently

Can we find cycles in Twitter discussions ?

# MEASURING CONTROVERSY BETWEEN ACCEPTED AND NON ACCEPTED TWEETS

Measuring controversy between  $S$  (accepted) and  $T \setminus S$  (non accepted) tweets:

- Number of defeaters in  $S$  and in  $T \setminus S$  (if both numbers are high and similar we can take it as a signal for high controversy)
- Controversy depth: How long are the discussion **alternating paths** (alternating between  $S$  and  $T \setminus S$ ) ?



## DISCUSSION ANALYSIS - EXAMPLES

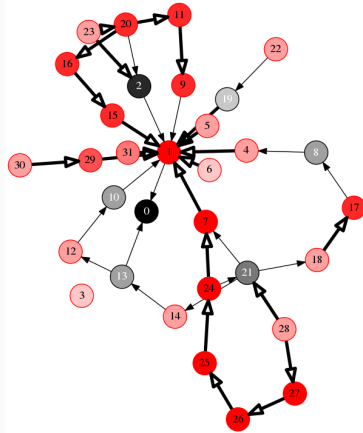
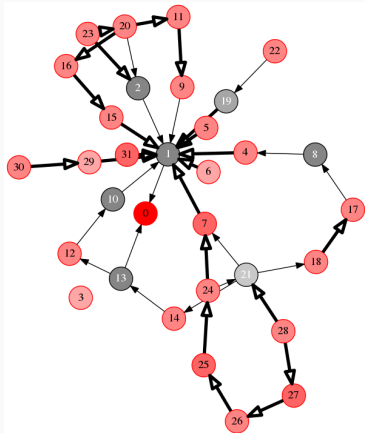
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## DISCUSSION ANALYSIS EXAMPLES - FOLLOWERS COUNT WEIGHT

Discussion URL, size	$ S $	$ d_{in} $	$ d_{out} $	$Contr_{depth}$	$\frac{\sum_{in} W}{\sum_{out} W}$	$ \Delta $
https://goo.gl/m4RON9, 32	0.78	7	4	6	4.44	
	0.78	7	4	8	4.89	2
https://goo.gl/NGEWrr, 57	0.92	4	0	5	14.33	
	0.92	4	0	5	23.88	0
https://goo.gl/ftyIJ7, 78	0.75	24	2	13	3.58	
	0.76	24	1	13	5.84	1
https://goo.gl/RnFJ39, 95	0.66	33	8	10	2.26	
	0.67	32	5	15	3.04	5

# DISCUSSION ANALYSIS EXAMPLES - FOLLOWERS COUNT WEIGHT

<https://twitter.com/jordievole/status/574324656905281538>



Solution

with support aggregation

When considering support (sum) aggregation, an attacker for root tweet gains more support than the root tweet

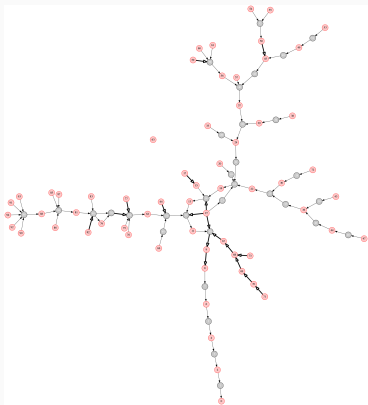
## DISCUSSION ANALYSIS EXAMPLES - RETWEETS COUNT WEIGHT

Discussion URL, size	$ S $	$ d_{in} $	$ d_{out} $	$Contr_{depth}$	$\frac{\sum_{in} W}{\sum_{out} W}$	$ \Delta $
https://goo.gl/m4RON9, 32	0.81	6	5	7	4.83	
	0.78	7	5	8	4.18	1
https://goo.gl/NGEWrr, 57	0.92	4	3	5	13.5	
	0.92	4	3	5	23.0	0
https://goo.gl/ftyIJ7, 78	0.70	66	49	14	2.47	
	0.74	41	13	21	4.60	15
https://goo.gl/RnFJ39, 95	0.65	47	32	12	1.87	
	0.67	40	27	11	2.42	8

The ratio  $\frac{\sum_{in} W}{\sum_{out} W}$  is smaller (than with followers count)

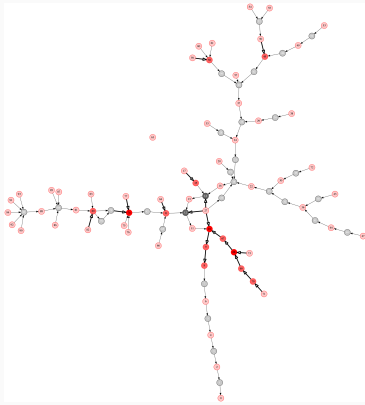
Support aggregation produces more differences in the solutions

<https://twitter.com/juanrallo/status/590480494636179456>



Solution

We have a significant controversy between accepted and not accepted tweets



with support aggregation

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