A Motif-based Approach for Identifying Controversy

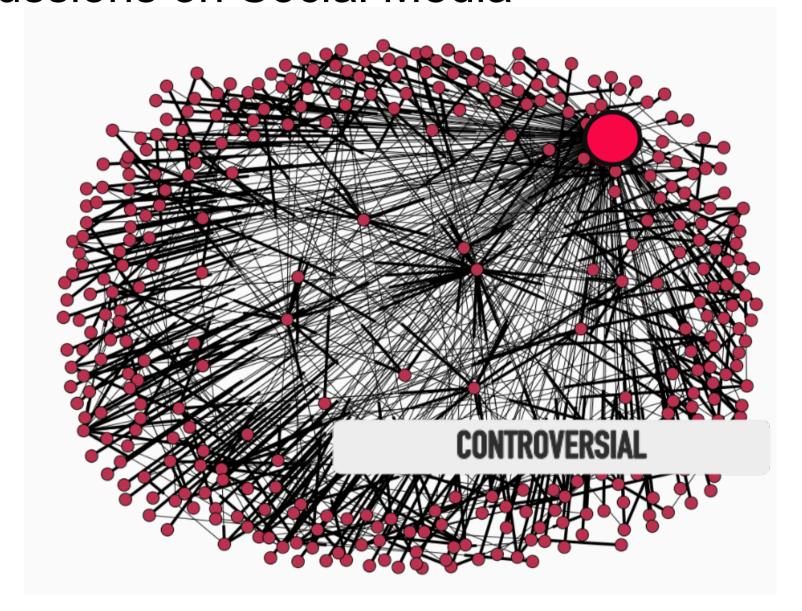
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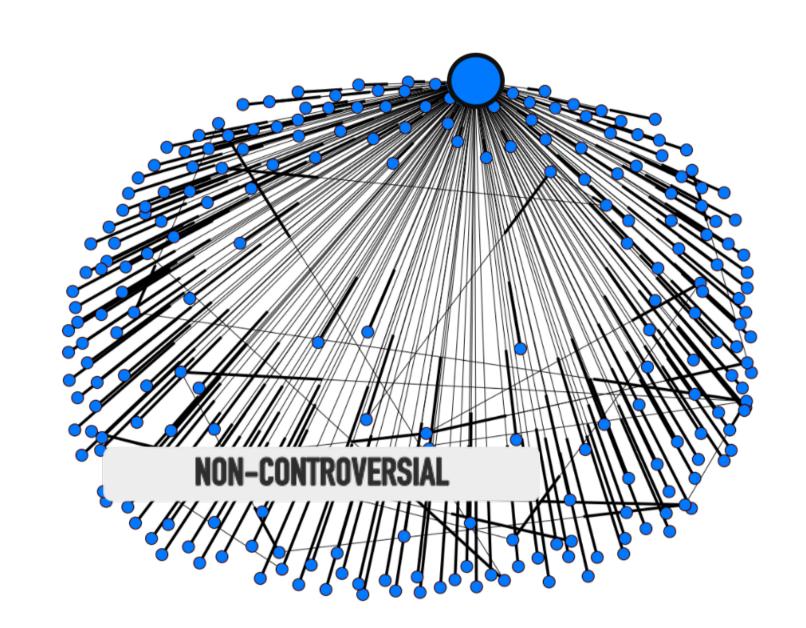
Goal

 Algorithmically identify controversial discussions on Social Media



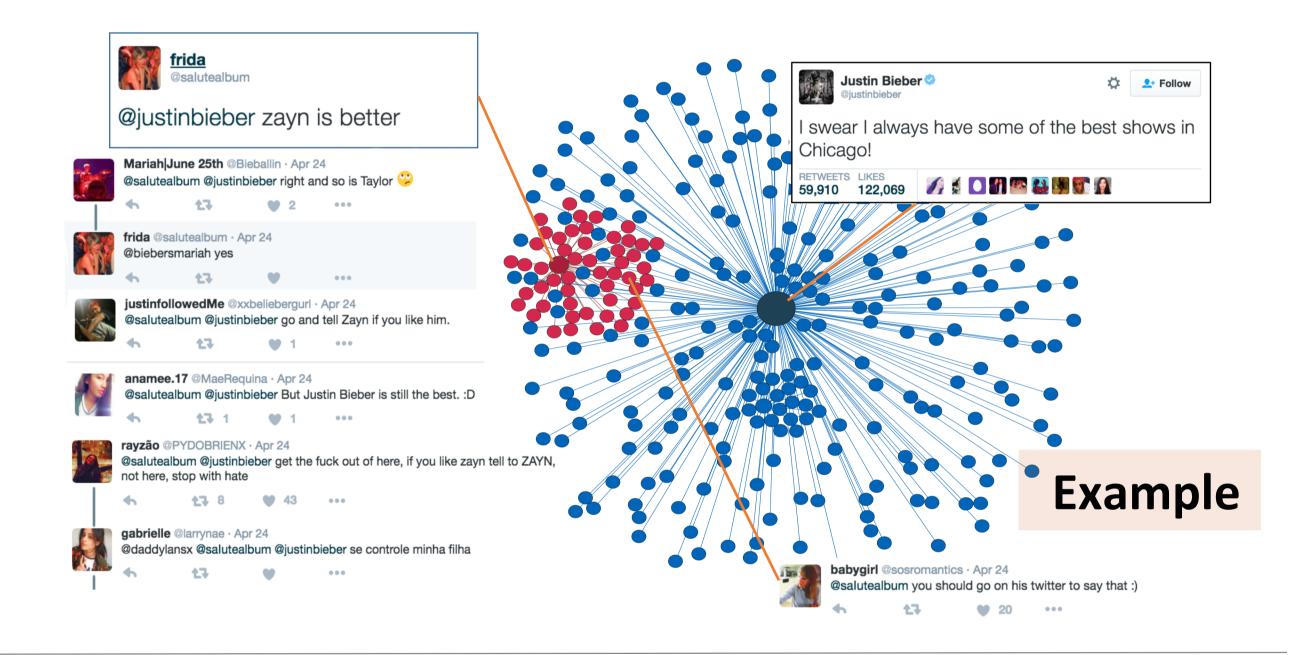
How

Exploiting network conversational motifs



Data Twitter pages Root posts Tot. tweets Filtering Avg. users 1202 192.7K108 >2 users 1175 (97%) 192.5K>3 users 110 1046 (87%) 123191.3K>10 users

Controversial	 @tedcruz, @mov5stelle, @brexitwatch @barackobama, @realdonaldtrump @wikileaks, @berniesanders, @cnnbrk @bbcworld, @hillaryclinton, @potus 	
Non Controversial	@coldplay, @justinbieber, @cristiano @adele, @chanel, @xbox, @nba	

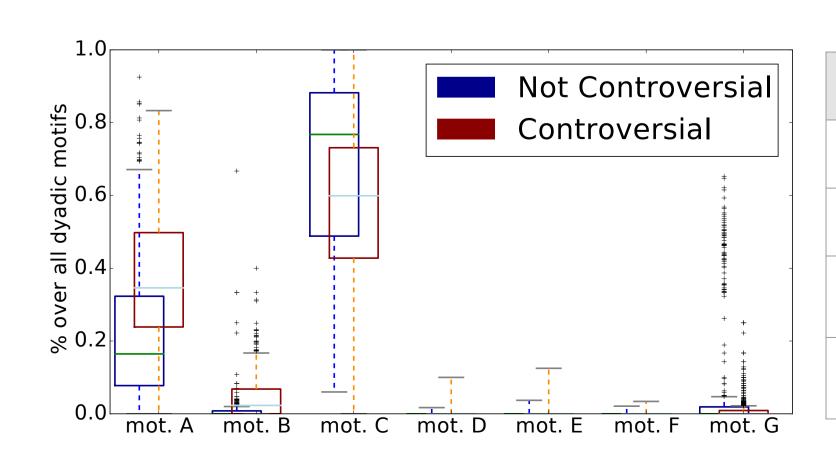


Detail

- Features extracted from the User Graph and from the Reply Tree:
 - O Structural e.g. Average Node Degree
 - Propagation based e.g. Average Cascade Depth
 - Temporal e.g. Average Inter-reply Time
 - **Conversational Motifs** Dyadic and Triadic
- Machine-Learning model: ADA BOOST, casted into a classification problem

DYADIC MOTIFS A O C O E O F O G Feblies to G Follows TRIADIC MOTIFS

Results:



Method	Accuracy	Precision	Recall	F-measure
Baseline	0.78	0.81	0.83	0.82
Dyadic motifs only	0.77	0.79	0.84	0.82
Baseline + dyadic motifs	0.84	0.86	0.88	0.87
Baseline + dyadic and triadic motifs	0.85	0.87	0.88	0.87

Best features

- 1- Avg. inter-reply time
- 2- Max. relative degree
- 3- Motif A
- 4- % Replies within 1h
- 5- **Motif B**
- 6- Motif G

+ 6%