



Detection and Delineation of Events and Sub-events in Social Networks



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MOTIVATION



In real life, a series of highlights (sub-events) constitute an event

E.g., a soccer game can be described by a sequence of sub-events (goals, penalties, cards, halftime, etc) or a music show can be described by the sequence of the artists' appearances

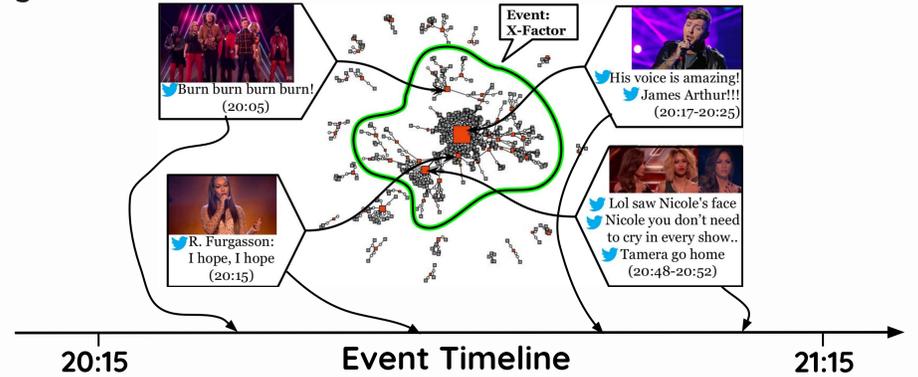
However, Event Detection techniques report and treat events as *singletons*

We introduce **Event Delineation** to better analyze, understand and narrate what happened

DELINEATION

Event Delineation is the breakdown of an event into its sub-events

E.g., The X-Factor music show:



DEFINITIONS

i) **Snapshot of a Dynamic Network**, $G_t = \{V_t, E_t\}$, with $V_t = V_{u,t} \cup V_{c,t}$, where $V_{u,t}$ is the set of user nodes and $V_{c,t}$ is the set of content nodes at time t , $E_t \subseteq V_t \times V_t$

ii) **Event**, $\Gamma = \{R_\Gamma, T_\Gamma, S_\Gamma\}$, where:

R_Γ : a representative summary (e.g., text description),

T_Γ : the time duration of the event, and

S_Γ : a set of sub-events

iii) **Sub-Event**, $\gamma_n = \{r_{\gamma_n}, t_{\gamma_n}\}$, where:

r_{γ_n} : representative summary, t_{γ_n} : timestamp of the sub-event

iv) **Problem: Event Detection and Delineation**

Given a Content Network $G = \{G_t \mid t=0, \dots\}$, find all events Γ with all their sub-events S_Γ

METHOD: DeLi

1) **Build snapshot network & Reveal hidden links**

$userX$ replies $userY$,
 $userX$ posts $textA$,
 $textA$ **similar_to** $textB$

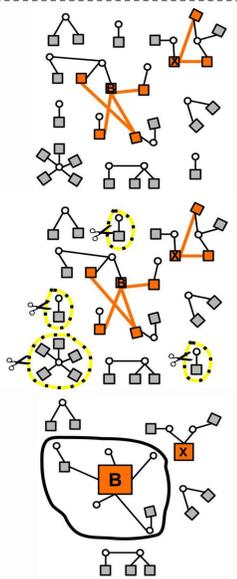
2) **Prune noise and spam**

repetitive incidents
& star structure CCs

3) **Detect events and sub-events**

events \rightarrow very large CCs
sub-events \rightarrow central content nodes in vCCs

$$h(CC_i) = \begin{cases} 1, & \text{if } |CC_i| > \text{avg}(|CC|) + \theta * \text{std}(|CC|) \\ 0, & \text{otherwise} \end{cases}$$



EXPERIMENTS

1) **Dataset:** ~ 700K public geotagged tweets from London organised into 15-min time windows

Ground truth: Wikipedia & manual annotation

2) **Event Detection**

Act: unexpected #tweets

Struct: unexpected CC size

based on network's structure (only user nodes)

DeLi_{Con}: unexpected CC size

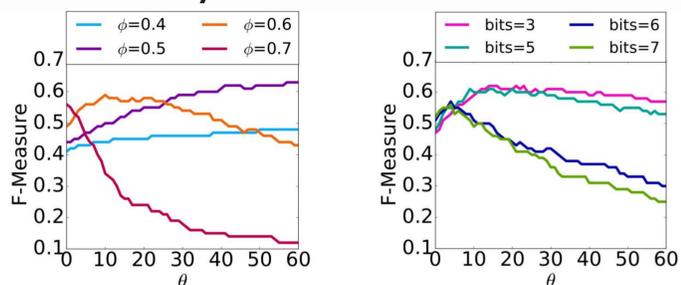
based on network's structure (only content nodes)

DeLi_{Ter}: unexpected CC size on the *Term Graph*

DeLi: using tfidf vectors for revealing similar links

DeLi#: using SimHash for revealing similar links

3) **Parameter Study:**



- Left: DeLi's F1-score for varied values of θ and ϕ (cosine similarity threshold)

- Right: DeLi#'s F1-score against θ and #bits (the SimHash fingerprint size)

4) **Sub-Event Detection:**

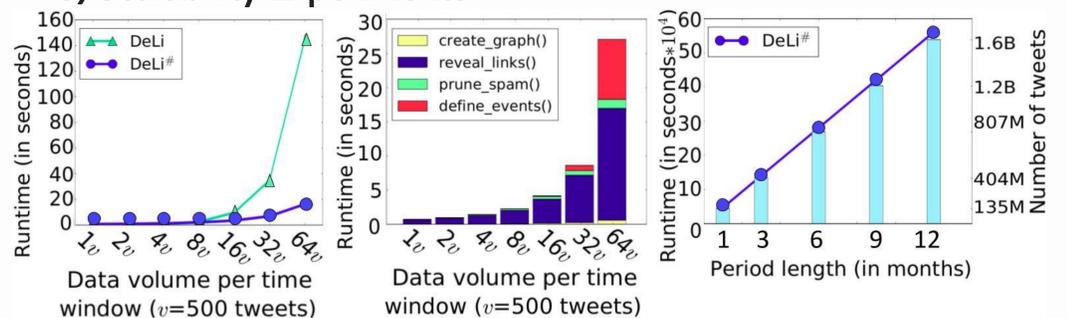
State-of-the-art: K-Cores utilizes the Term Graph and ranks events using the k-core score

Method	Precision	Recall	F-Score	Runtime
K-Cores (1-min)	0.14	0.19	0.16	-
K-Cores (15-min)	0.2	0.03	0.05	11091s
DeLi	0.15	0.49	0.22	139s

The fraction of sub-events of each type detected by each method

Sub-Event Type	Ground Truth	DeLi 15-min	K-Cores 1-min	K-Cores 15-min
Total goals	86	0.70	0.33	0.05
Penalties	3	0.33	0.0	0.0
Own goals	6	0.83	0.17	0.0
Yellow cards	85	0.17	0.01	0.0
Red cards	1	1.0	1.0	0.0
Final Score	29	0.72	0.31	0.07
All Sub-Events	210	0.49	0.19	0.03

5) **Scalability Experiments:**



- Left: Varying volume per time window

- Center: Execution time of each module

- Right: Varying time period (static volume per time window)

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