



# Social Networks Popularity

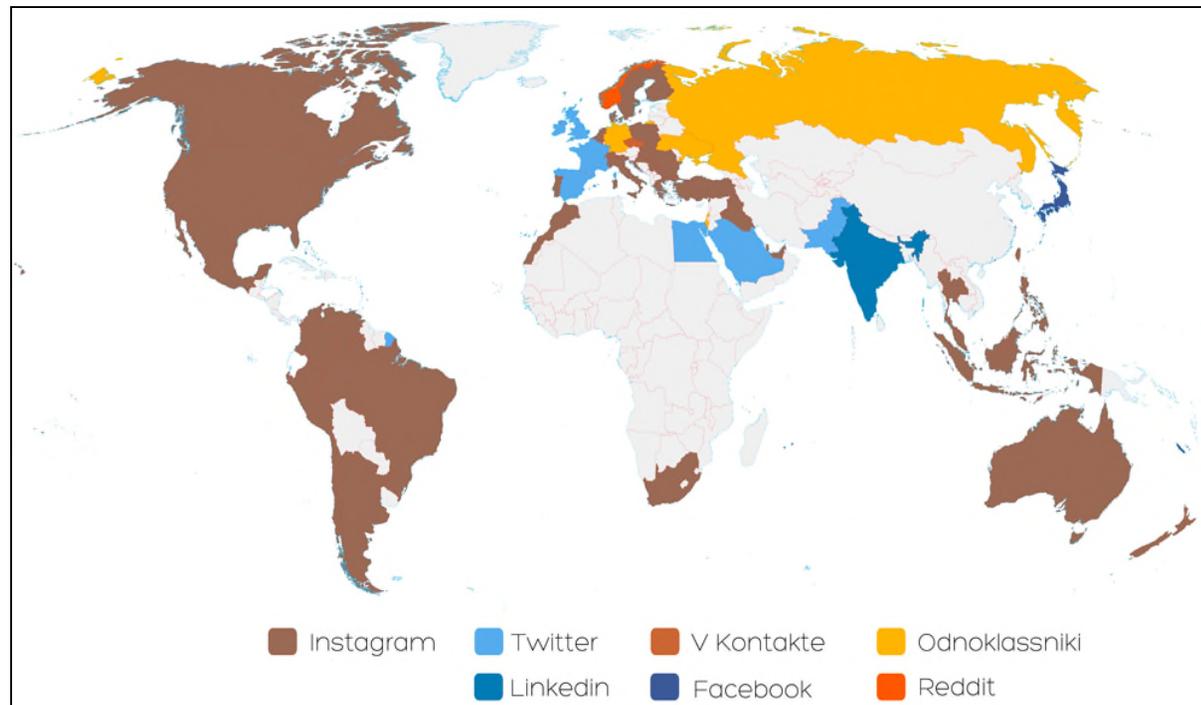
- Facebook is the leading social network in 129 countries
- Around 1.6 billion active users
- Content is mostly private and not accessible for general browsing.



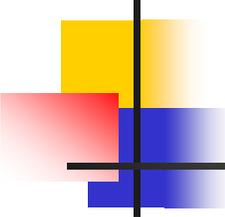
1<sup>st</sup> ranked social network in each country

# Social Networks Popularity

- Most popular image sharing network
- 600m monthly active users & 80m image uploads per day
- Content is publicly available via few web sources



2<sup>nd</sup> ranked social network in each country



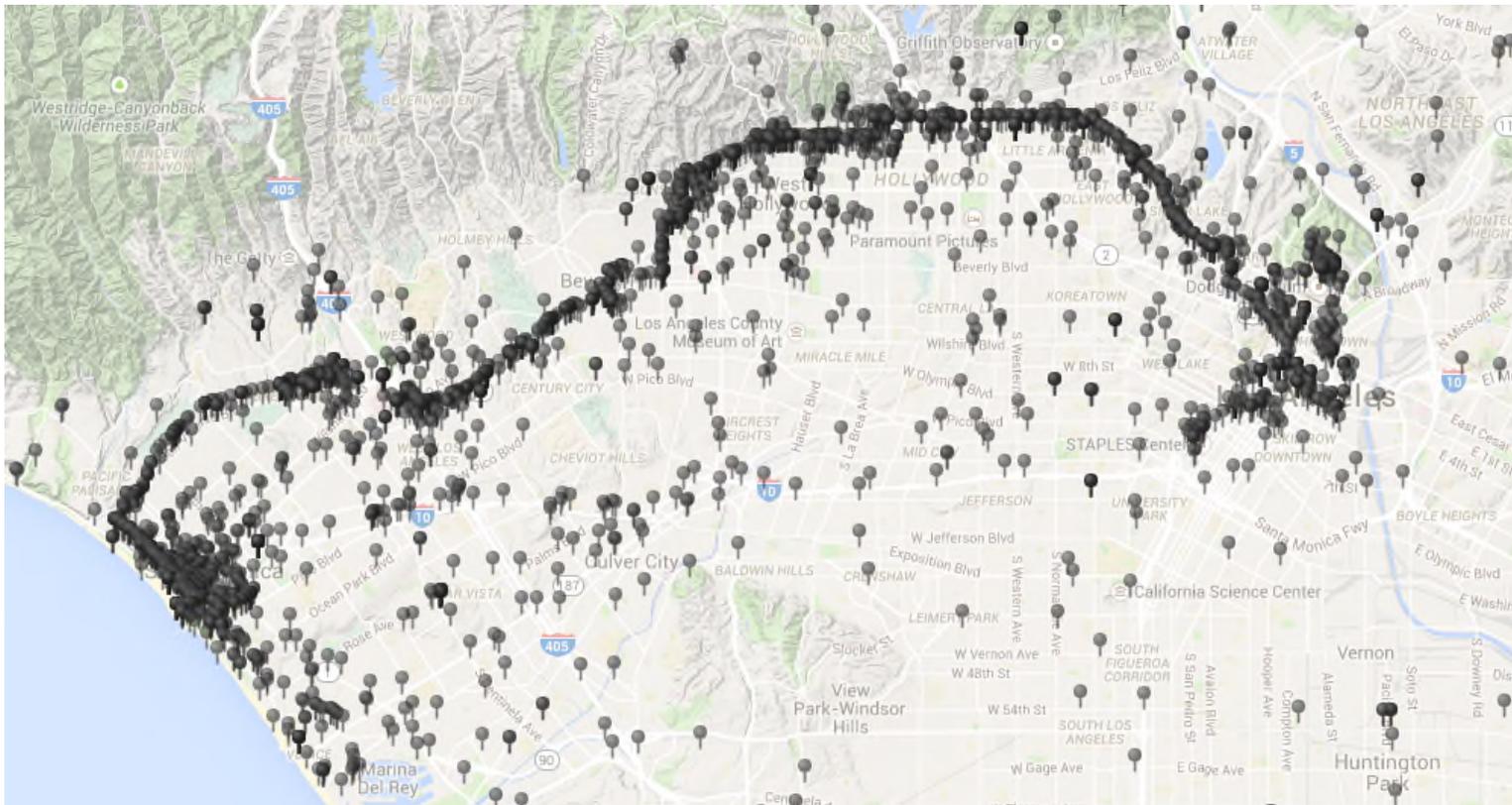
# Detection, Localization and Tracking with Instagram

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- *Motivation:* Why use Instagram for Event Localization?
  - Unlike text that can be written from anywhere, pictures of an event are generally taken at the event location.
  - Almost 25% of Instagram images are geotagged (but only 2% of tweets).
- *Analogy:* An Instagram picture = “binary sensor” signifying event “detection”
- *Method:* Leverage prior sensor network literature on localization and tracking with binary sensors

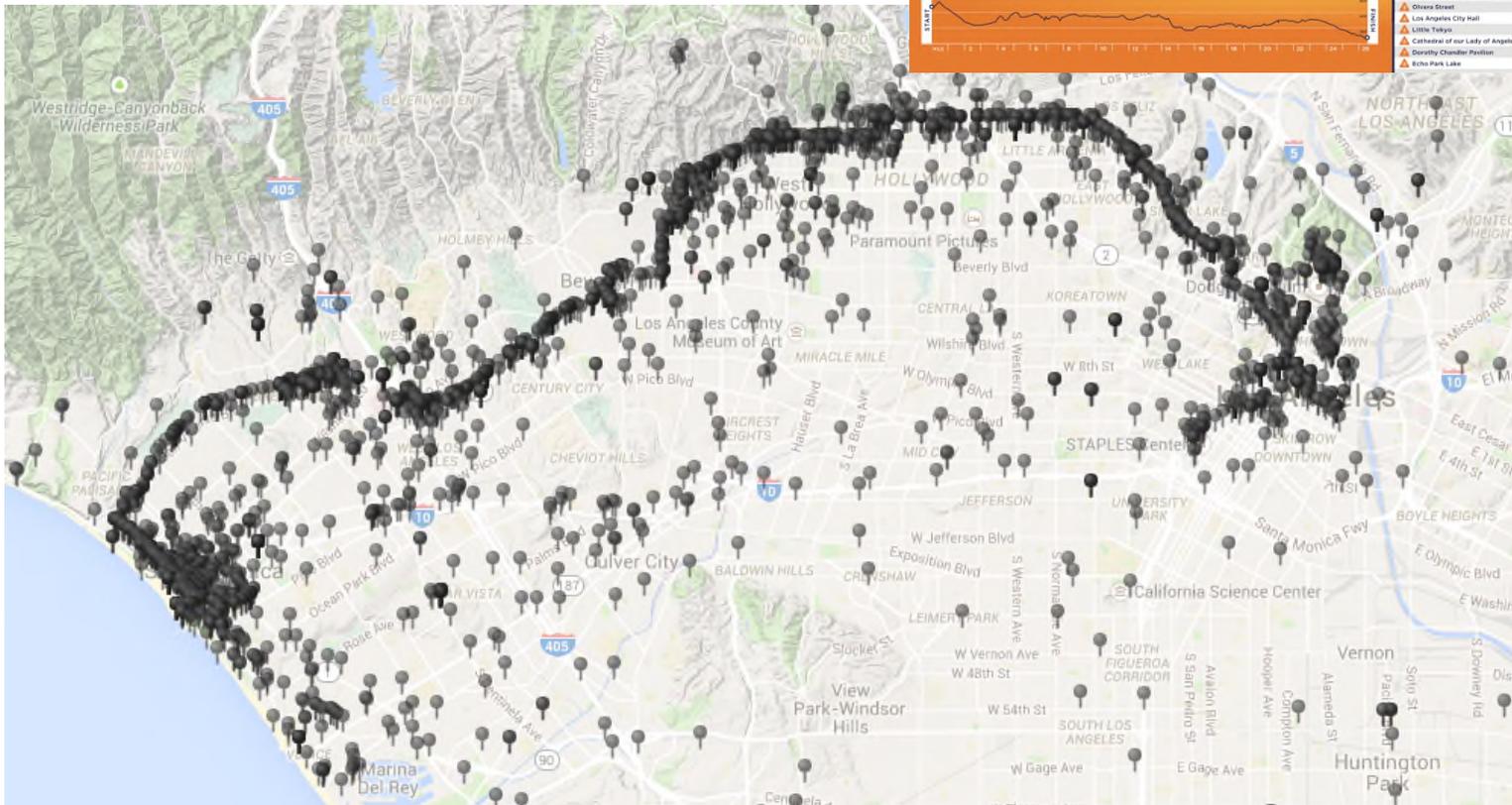
# Feasibility of Instagram-based Localization

- Example: Tracking “LA Marathon” (2015)



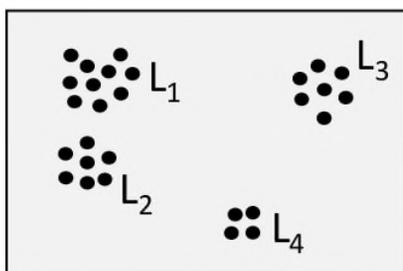
# Instagram

## Tracking "LA Marathon"

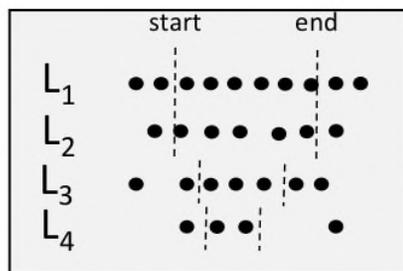


# Instagram Event Detection

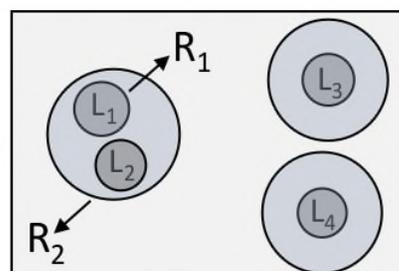
- Paper accepted to Infocom 2017



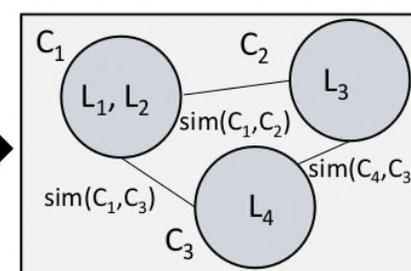
Step 1: Process the data from API and arrange locations in decreasing order of unique users and images.



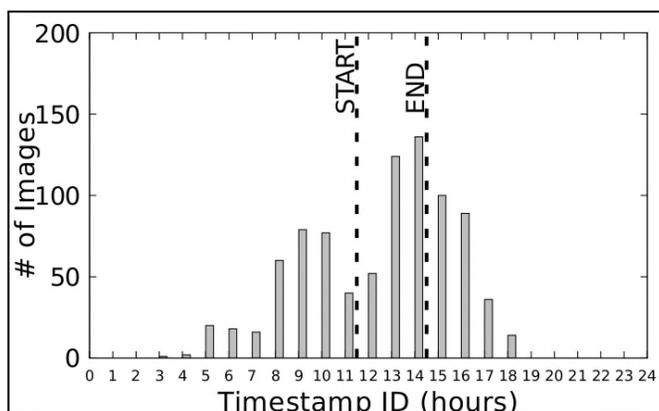
Step 2: Estimate the start and end times for each location using the time distribution of the posts.



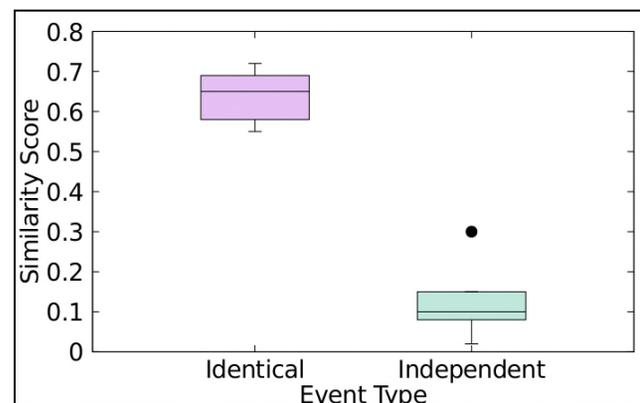
Step 3: Determine the best clustering range using the silhouette score and group the locations.



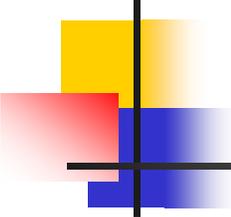
Step 4: Eliminate the false positive clusters by finding the similarity between the top ten hash tags.



Estimated start and end times of an event



Similarity using hash tags between clusters



# Event Detection Results

TABLE V. RECALL

Dataset	Our Localization Algorithm	Tag Similarity Localization				Geo Event Detection [23]				Points of Interest [5]
		$X = 20\%$	$X = 40\%$	$X = 60\%$	$X = 80\%$	$\theta = 0.2$	$\theta = 0.4$	$\theta = 0.6$	$\theta = 0.8$	
Taylor Swift	28/28	24/28	25/28	26/28	26/28	28/28	28/28	28/28	28/28	27/28
Maroon V	17/17	13/17	15/17	17/17	17/17	17/17	17/17	17/17	17/17	17/17
Marathon	5/5	3/5	4/5	4/5	4/5	5/5	5/5	5/5	5/5	5/5
Tornado	3/3	2/3	3/3	3/3	3/3	3/3	3/3	3/3	3/3	3/3

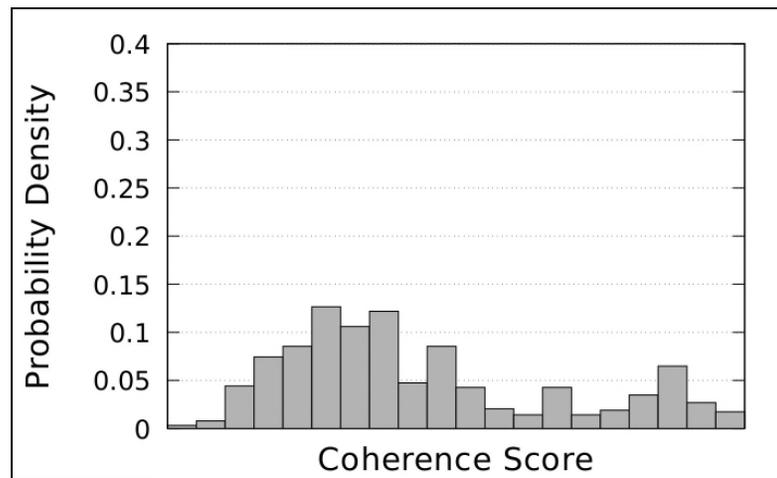
TABLE VI. FALSE POSITIVES

Dataset	Our Localization Algorithm	Tag Similarity Localization				Geo Event Detection [23]				Points of Interest [5]
		$X = 20\%$	$X = 40\%$	$X = 60\%$	$X = 80\%$	$\theta = 0.2$	$\theta = 0.4$	$\theta = 0.6$	$\theta = 0.8$	
Taylor Swift	2	18	10	5	4	35	16	9	9	26
Maroon V	0	5	4	4	2	19	8	8	8	14
Marathon	0	16	10	7	6	17	11	11	11	15
Tornado	1	3	3	3	2	6	6	6	6	19

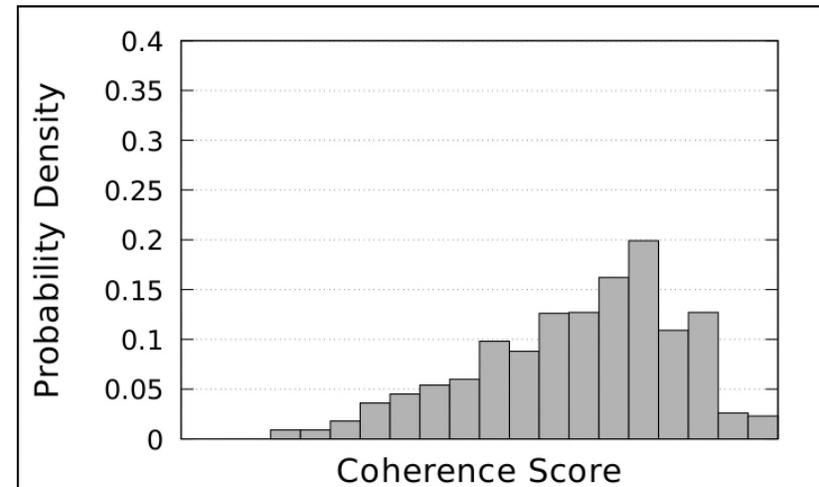
# Combined Detection from: Twitter + Instagram

Instagram Location	Instagram Tags	Tweets	Event Signature
(39.045417, -95.721562)	['picket', 'brainwashed', 'westboro', 'protest', 'important', 'wbc', 'truth', 'spreadtheword', 'westborobaptistchurch', 'true', 'dontworrybehappy']	(1) you realize christians protest westboro baptists right is wrong (2) westboro baptist church really protest gunderson production laramie project put years ago (3) fisher westboro protest offers gunderson students opportunity show grizzly pride	(westboro, protest)
(37.7870288, -122.407553)	['protest', 'themission', 'gentrification', 'valenciacorridor', 'googlebus', 'displacement']	(1) laylamrazavi el desalojo ya basta protest googlebus displacement gentrification valenciacorridor (2) video tech workers displaced googlebus protest catch another bus (3) tech buses blocked 45 minutes 2 yrs amp 2 months 1st googlebus protest sfbos sfmayor sb50	(googlebus, protest)

# Combined Detection from: Twitter + Instagram



Non events



Events

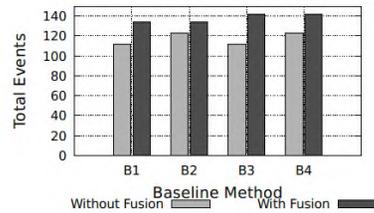
$$P(C|R = 1) = B(\alpha_1, \beta_1, C)$$

$$P(C|R = 0) = B(\alpha_2, \beta_2, C)$$

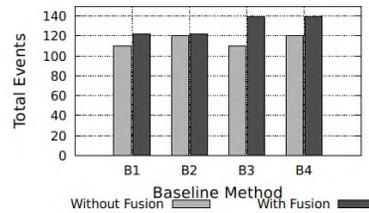
$$P(R = 1|C, L) = \frac{P(L|R = 1)P(C|R = 1)P(R = 1)}{\sum P(L|R)P(C|R)P(R)}$$

# Combined Detection from: Twitter + Instagram

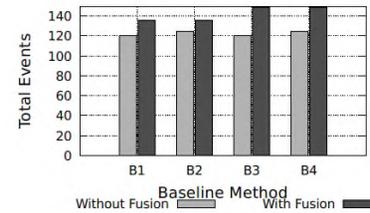
- Fewer false-positives than Twitter
- Better recall than Instagram



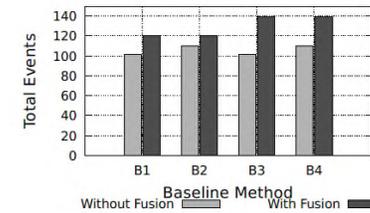
(a) Week 1



(b) Week 2

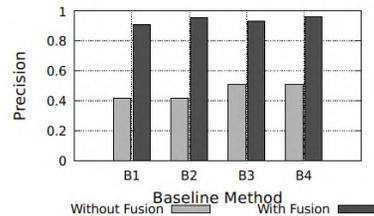


(c) Week 3

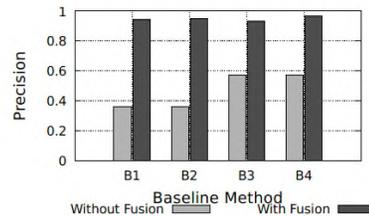


(d) Week 4

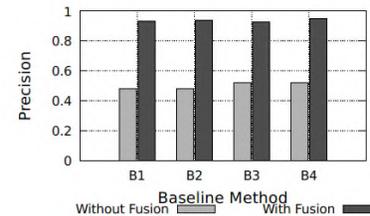
Instagram detection improvement - comparison of different baseline methods with and without fusion method



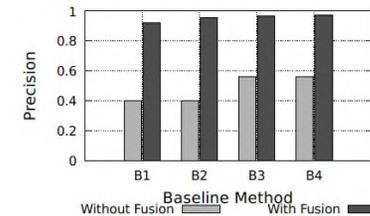
(a) Week 1



(b) Week 2



(c) Week 3

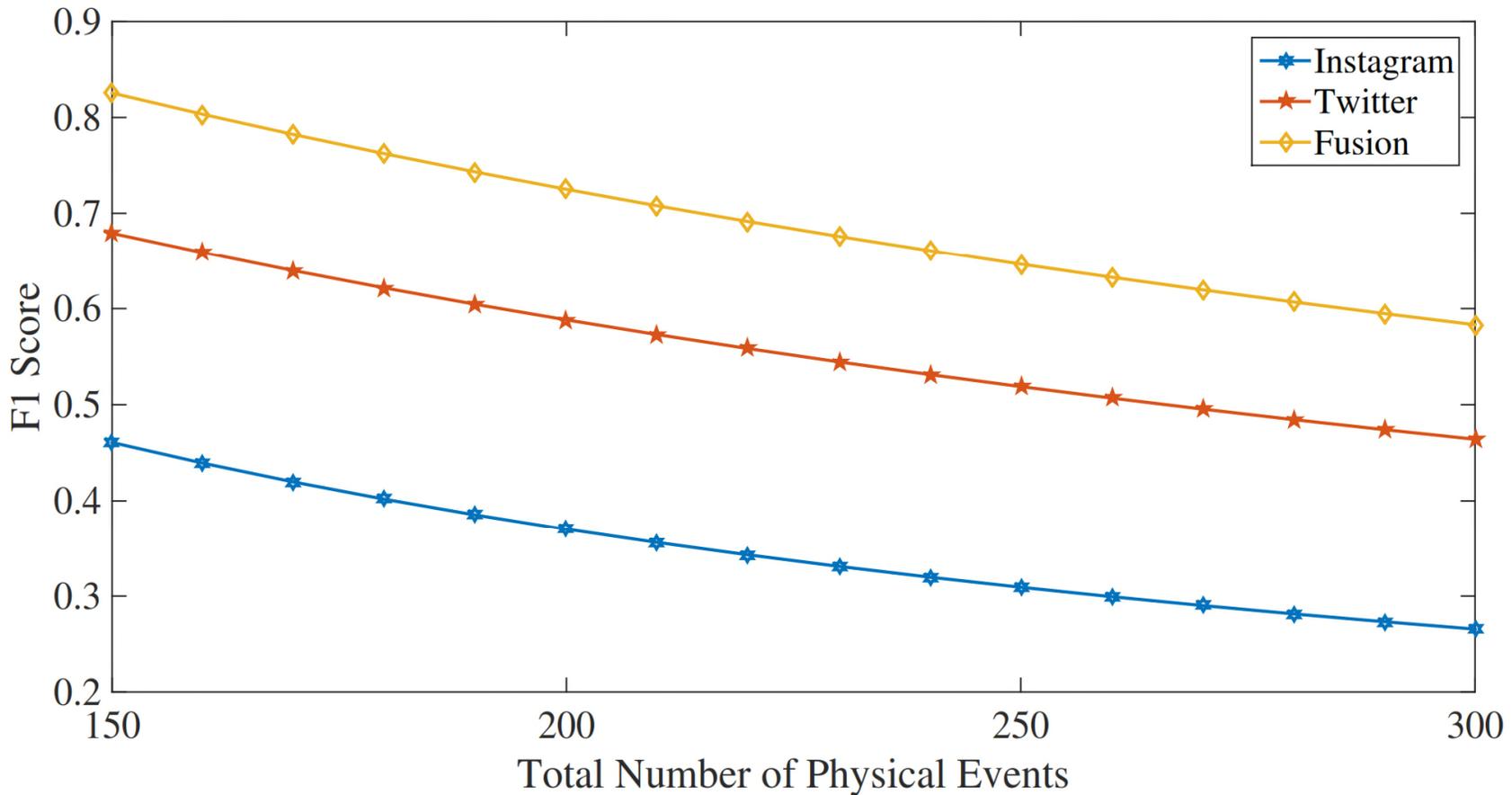


(d) Week 4

Twitter detection precision - comparison of different baseline methods with and without fusion method

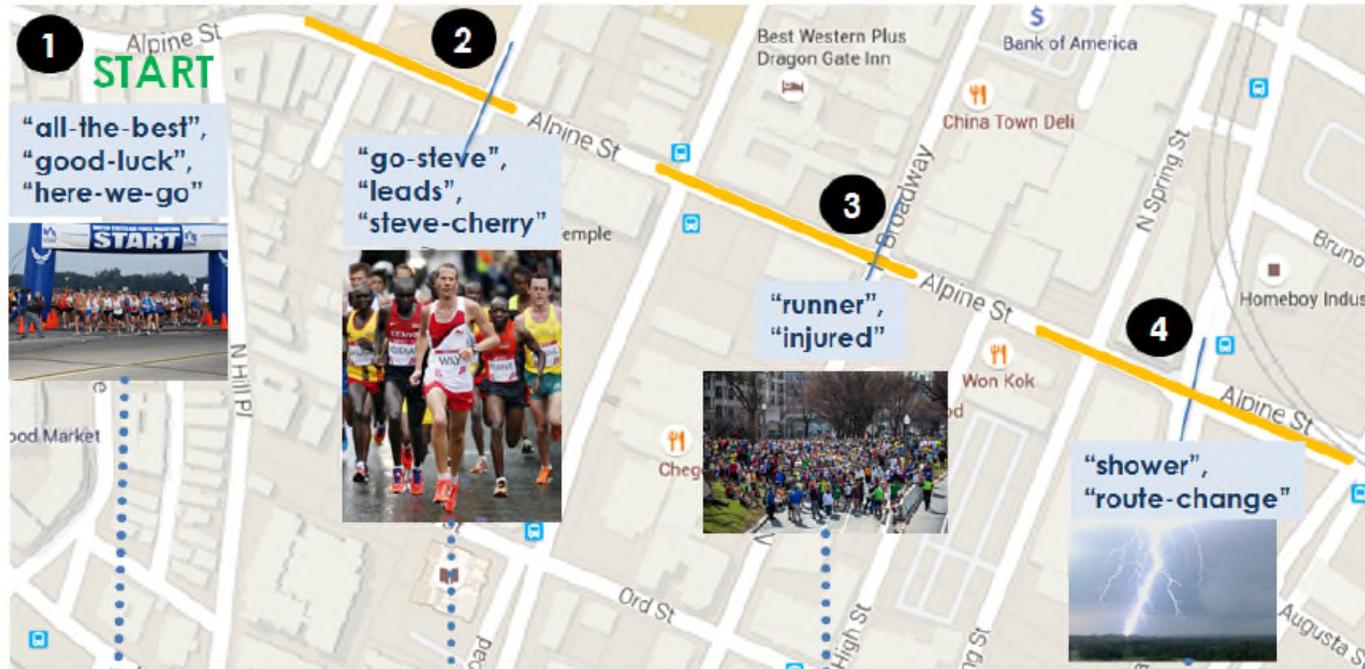
# Better Trade-off between Precision and Recall

■ F1 score

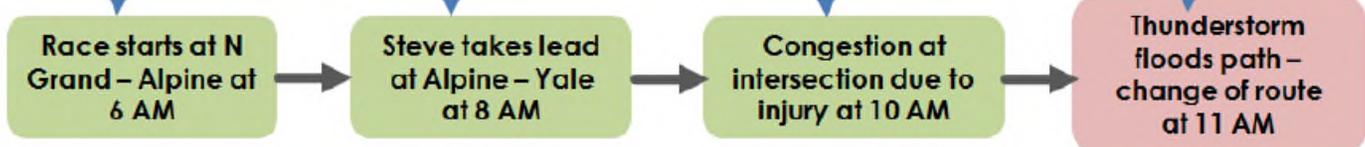


# Detection of Micro Events

MULTI-MODAL INFORMATION



INFERRED TRAJECTORY

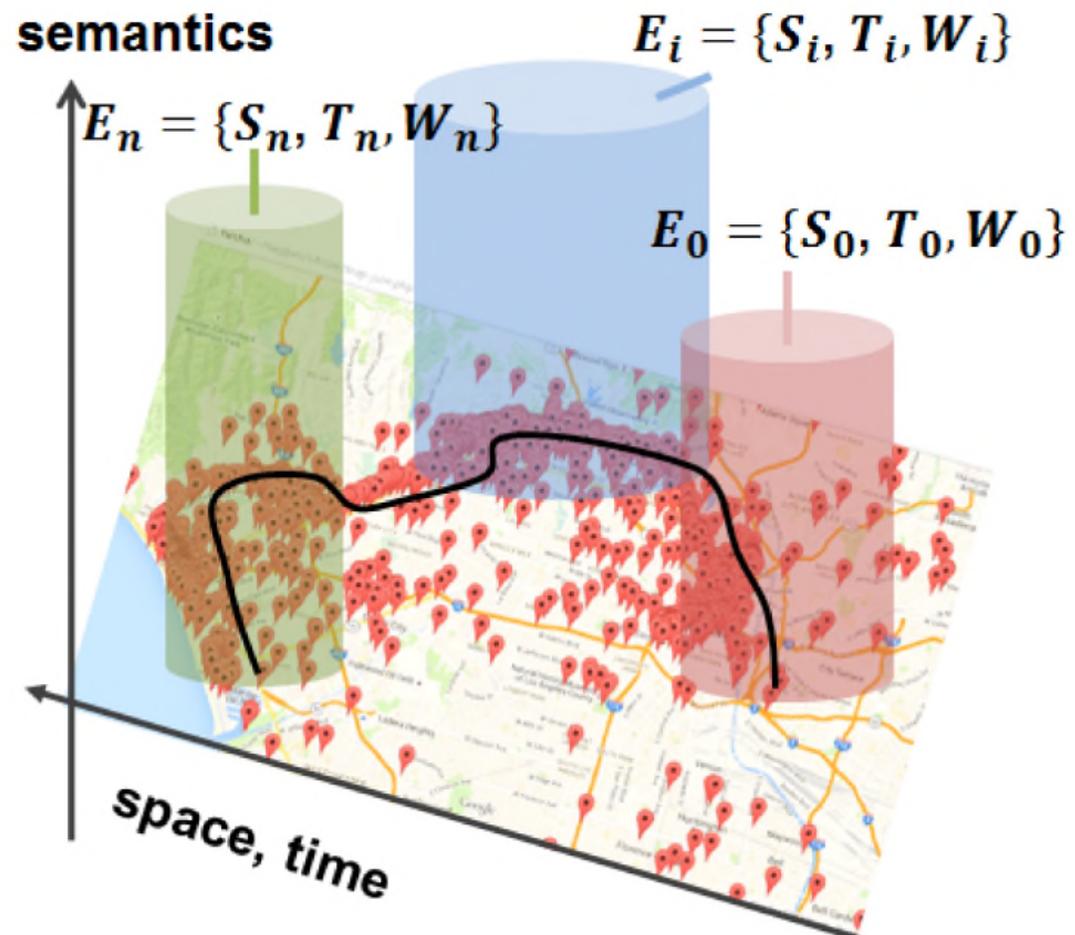


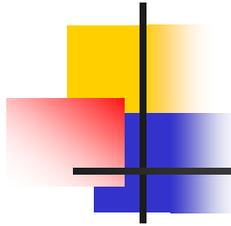
EXPECTED TRAJECTORY



# Event Representation

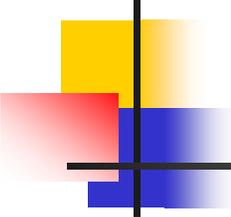
- A series of posts, each with location, time, and semantic tags





# What are Key Challenges?

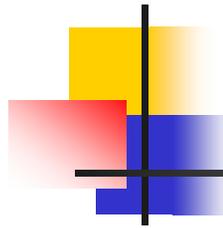
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# What are Key Challenges?

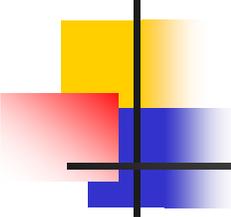
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- Boundaries vary by event (different temporal and spatial scales)
- Many posts are not relevant
- Image semantics are important
- Credibility varies



# Approach

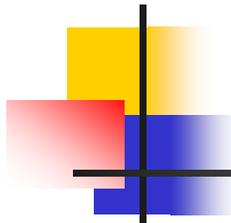
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# Approach

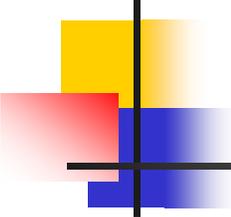
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- Apply relevance filter
- Extract semantic labels for images
- Represent the bag of word by a vector
- Cluster features (time, location, and word vector) by similarity



# Data

Category	Observation Period	Keywords Used for Filtering
<b>Marathon Events</b>		
Boston	April 2015	“bostonmarathon”, “baa”
LA	March 2015	“lamarathon”
London	April 2015	“londonmarathon”, “vmlm”
<b>Other Event</b>		
F1 SGP	September 2015	“f1 ”, “race(s) ”, “racing ”, “formula”
<b>Non-Events</b>		
Food	September 2015	“food”, “yummy”, “recipe”, “delicious”
Pets	September 2015	“dog(s) ”, “cat(s) ”, “puppy ”, “doggy”
Fashion	September 2015	“fashion”, “style”, “trend”, “outfit”
Selfies	September 2015	“selfie”, “friend”, “fun”



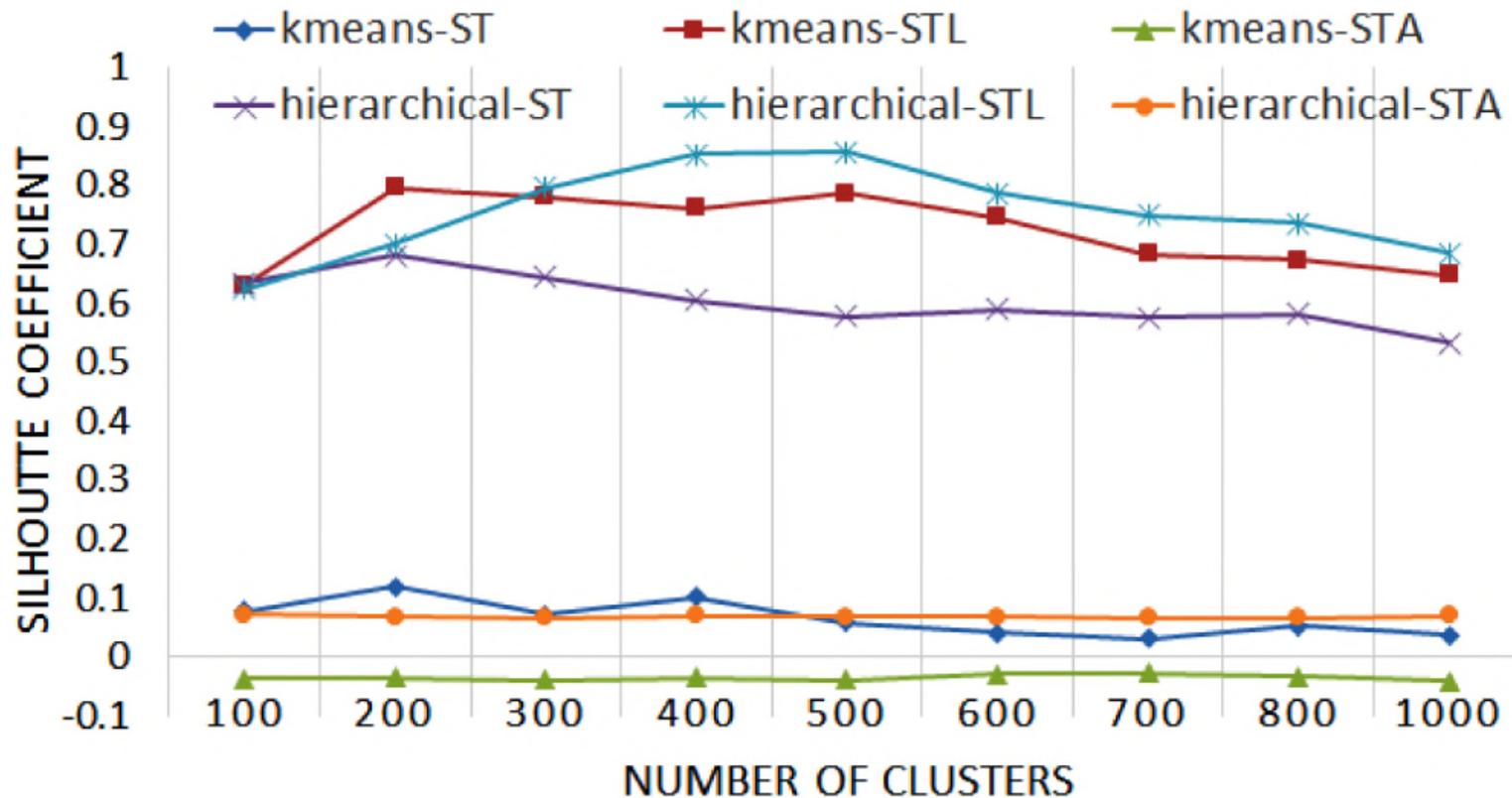
# Image Relevance

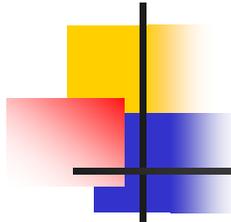
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- How to tell if an image is pertinent to the event?

# Clustering

- Quality of clustering

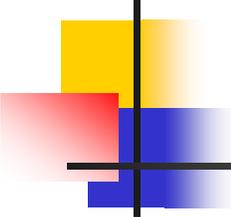




# Results

- Error in time and location for known micro-events

Micro-Event	Apprx. Location	Apprx. Time	Location Error in <i>km</i>		Time Error in <i>mins</i>	
			<i>ST+LDA</i>	<i>STA</i>	<i>ST+LDA</i>	<i>STA</i>
<i>Boston</i>						
Cheering	Hopkinton	8:50 - 11:15	5.22 (0.066)	13.03 (0.151)	66.93	68
Winners	Public Library	11:56 - 12:09	5.49 (0.062)	3.89 (0.047)	50.03	332.18
<i>London</i>						
Start of race	Greenwich Park	9:00 - 10:10	0.79 (0.027)	5.77 (0.079)	31.37	185.55
Winners	The Mall	11:43 - 12:14	2.70 (0.007)	5.44 (0.071)	57.03	56.46
<i>LA</i>						
Cheering	Dodger Stadium	6:30 - 6:55	3.62 (0.039)	3.88 (0.035)	93.01	99.53
Winners	Santa Monica	9:05 - 9:17	10.48 (0.094)	10.65 (0.098)	333.85	34.24



# Quiz

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- Which paper(s) on the reading list evaluate the efficacy of using *unlabeled data* to enhance learning/classification accuracy from smartphone sensor data?
- Paper:
- Purpose (Application):