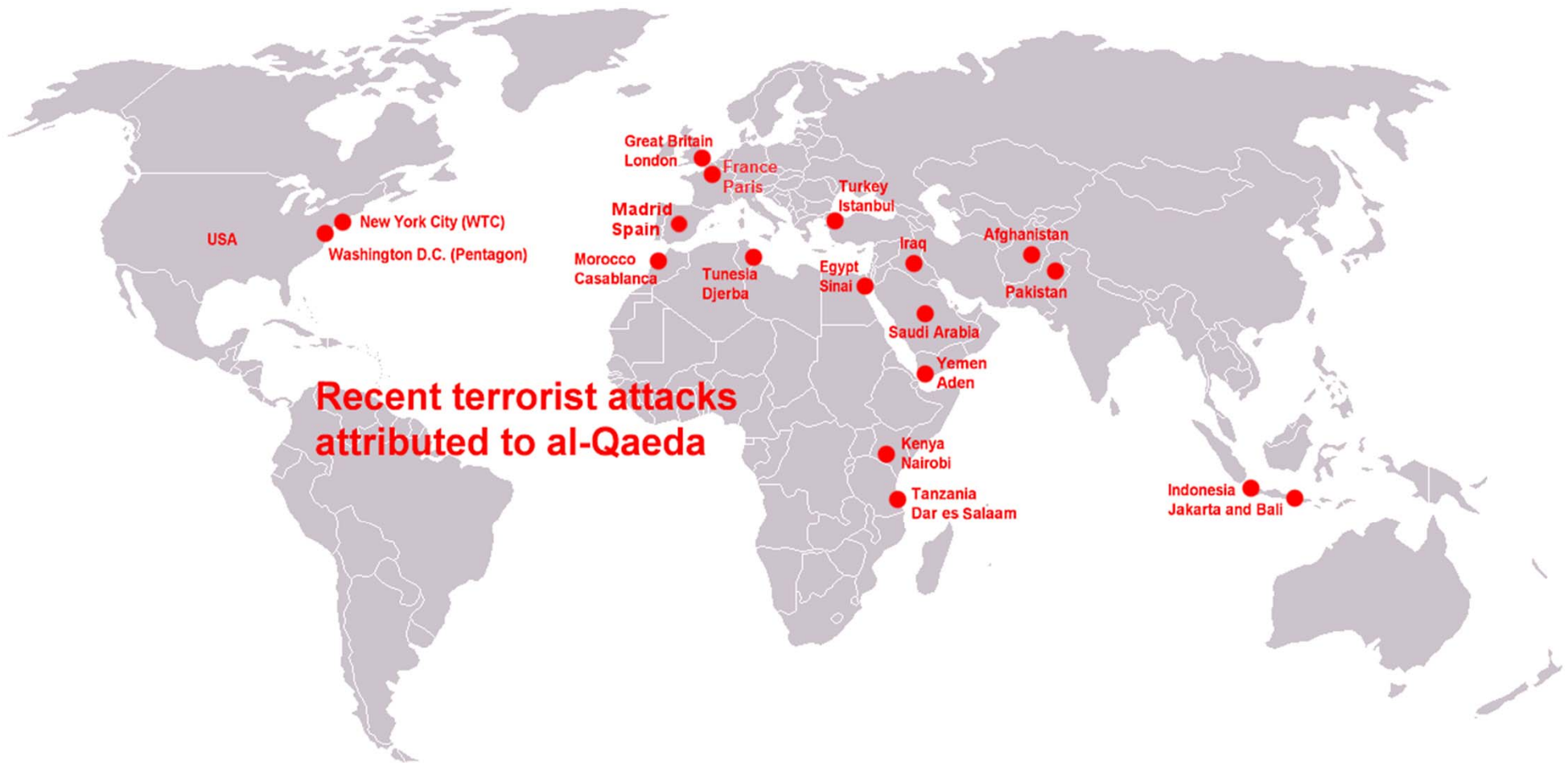




# Sensing Distress Following A Terrorist Event

Xidao Wen and Yu-Ru Lin  
University of Pittsburgh

# Problem



**Recent terrorist attacks attributed to al-Qaeda**

[Source](#)

# Research in Terrorism



Risk Prediction

Terrorism Risk Statistic/Probabilistic Modeling  
(Willis et al 2007, Laskey 2004, Hudson et al 2005, Jha 2009)



Impact Evaluation

- Economic Impact (Rose 2009)
- **Psychological impact** (Galea et al 2002, Lerner et al 2003, Shalev et al 2005)
- ...



[Source](#)

# Research Questions

## Analytical

- RQ1: How do people express their emotions immediately after the attacks?
- RQ2: How does people's emotional response evolve after the attacks?

## Computational / methodological

- Can we evaluate these questions in a timely manner?

# Method

# Dataset

- Computational focus group based on Geo-locations (Lin et al 2014) of Parisians.
- 16K users from Paris, ~4 million tweets
- 220k geo-tagged tweets



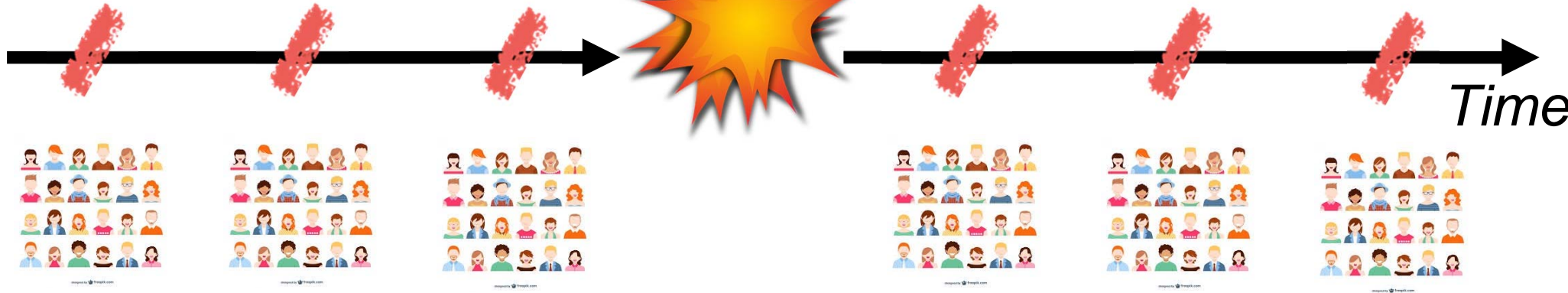




Twitter Users

Computational Focus Group

*Measurement*

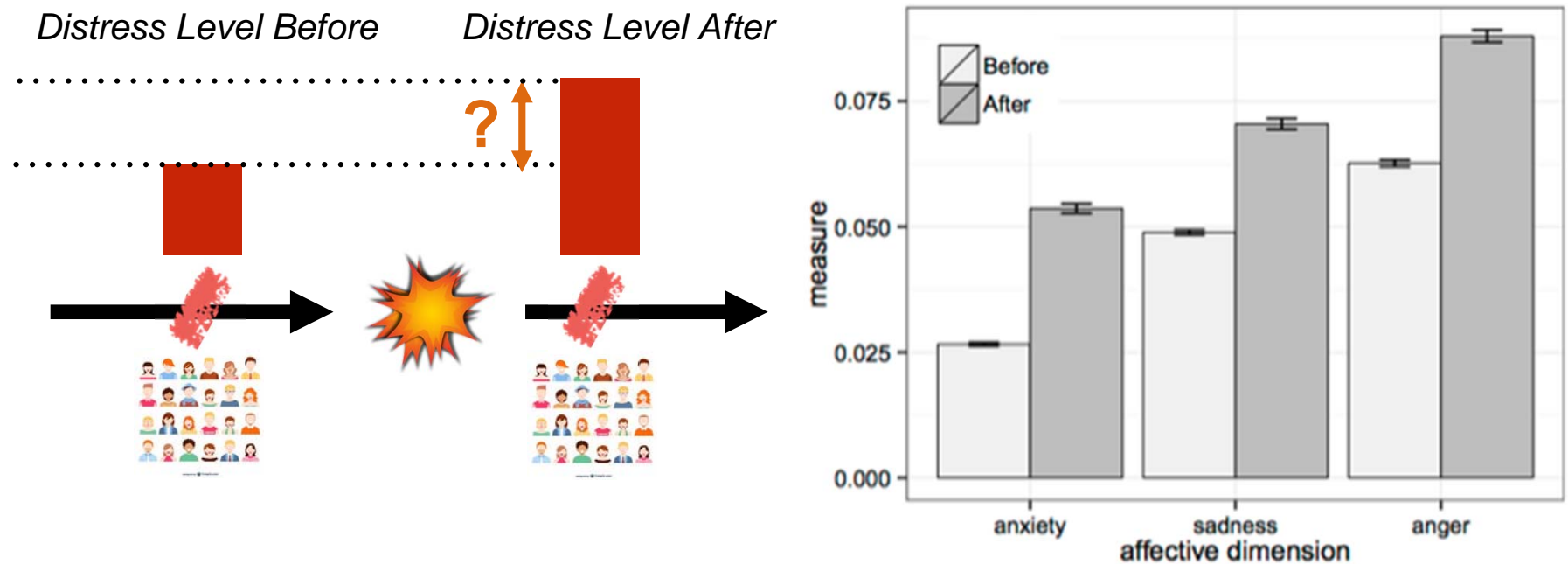


- Construct a computational focus group.
- Track behavioral measures for each user over time.
- Build and test Psychological and Sociological hypothesis.

# Defining Distress

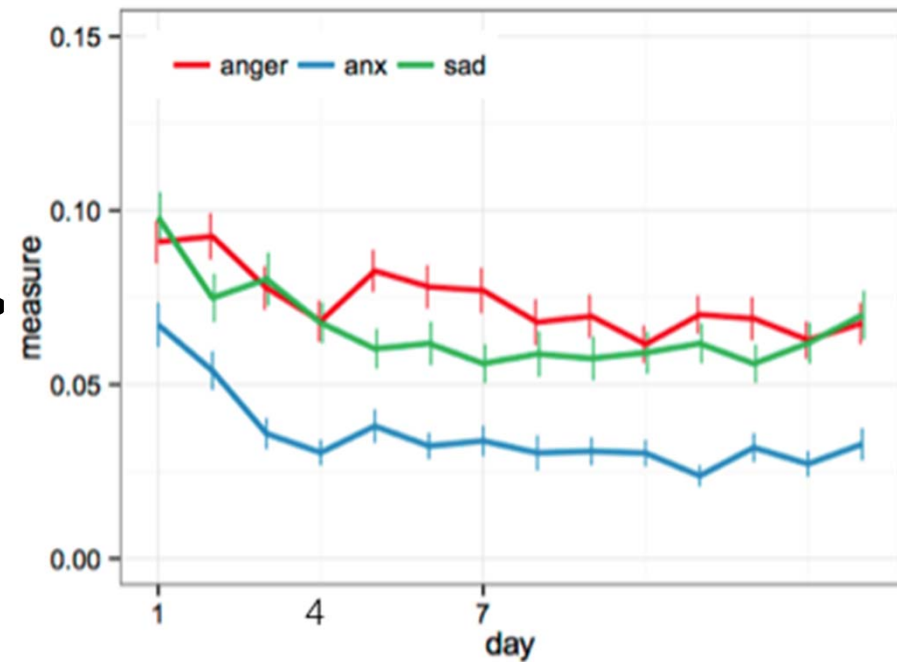
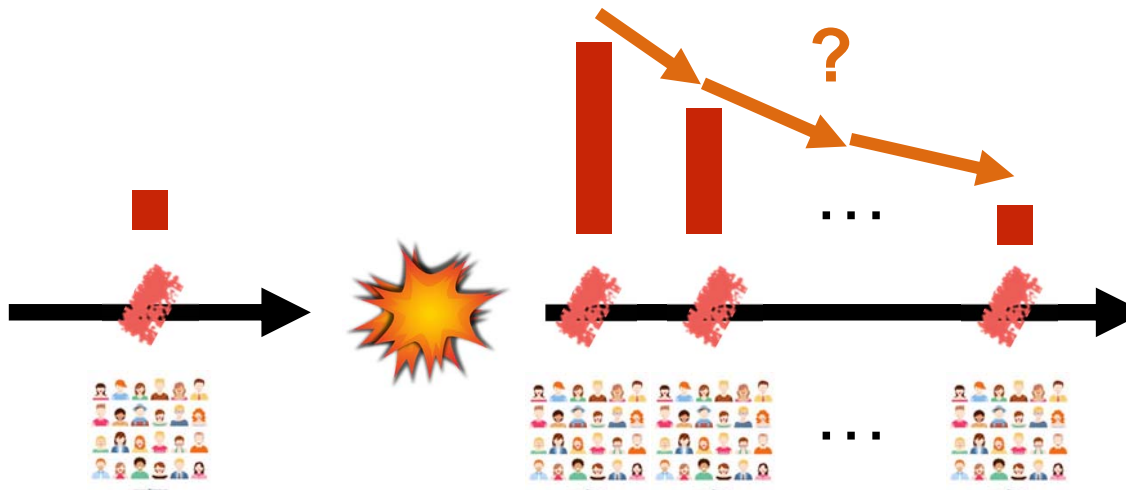
- Distress Response
  - or distress status as in three dimensions, ***anxiety, sadness, anger.***
  - measured by Linguistic Inquiry Word Count (LIWC) (Pennebaker 2001).
  - words in *Anxiety*: *worry, fearful, nervous, ...*
  - words in *Anger*: *hate, kill, annoyed, ...*
  - words in *Sadness*: *crying, grief, sad, ...*
- The proportion of tweets contain words in the LIWC lexicon of *anxiety, sadness, and anger* respectively.

- RQ1: How do people express their emotions immediately after the attacks?



Significant Increases in distress levels right after the attacks.

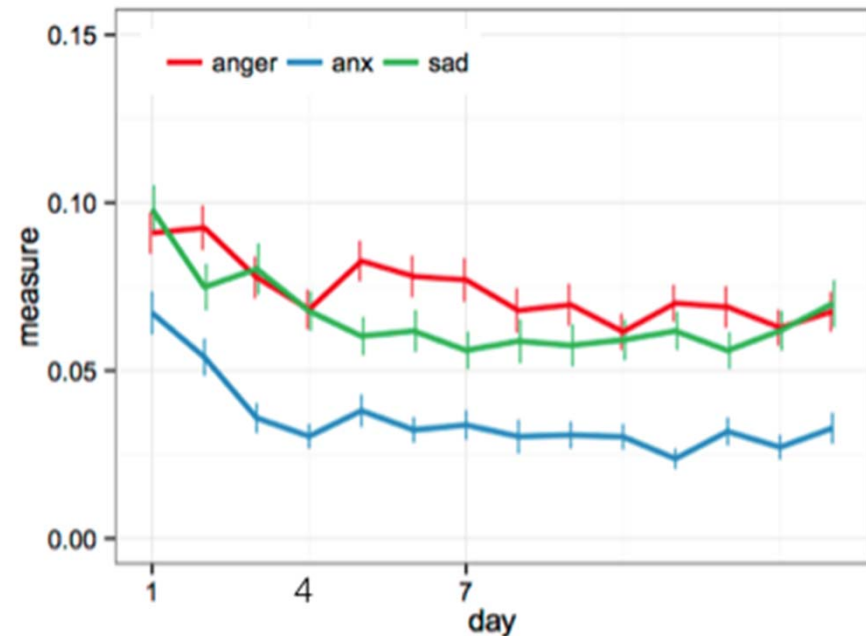
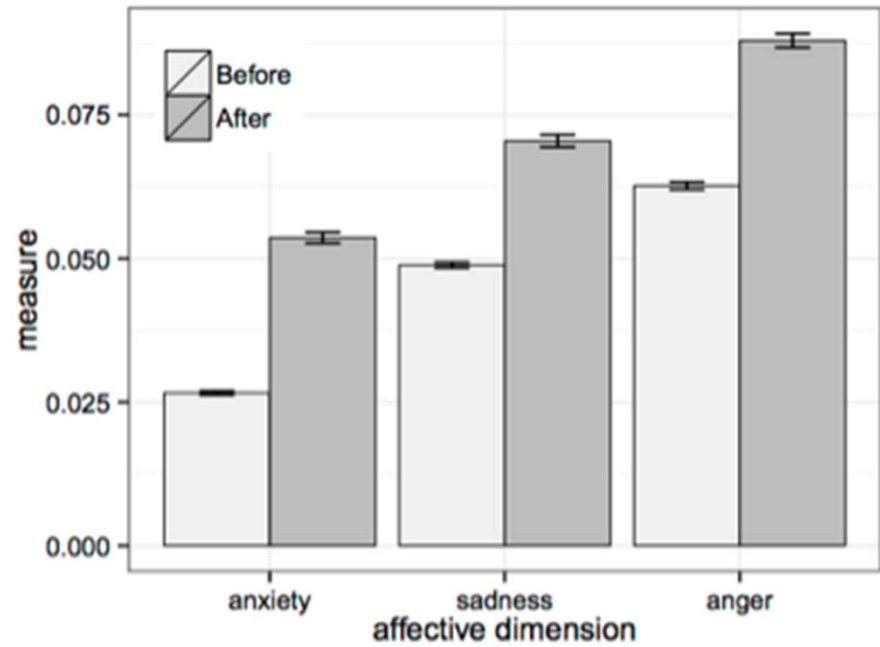
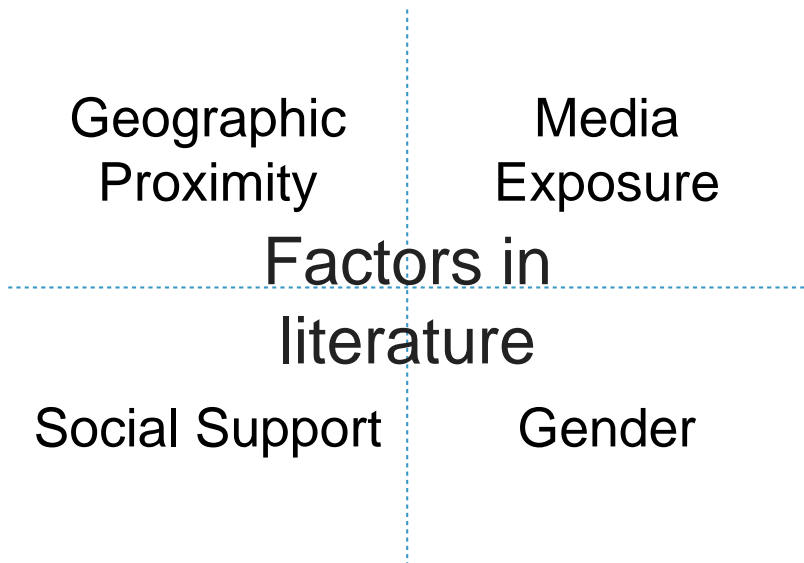
- RQ2: How does people's emotional response evolve after the attacks?







Distress levels fall back to stable pattern within seven days.



- How are individual differences associated with different distress responses?



# Results





	<i>Anxiety</i>	<i>Sadness</i>	<i>Anger</i>
Post-Geographical proximity	 **		
Media Exposure	 ***		 ***
Male		 *	

- How individual differences are associated with the immediate distress response?

\*\*\*,  $p < .01$

\*\* ,  $p < .05$

\* ,  $p < .1$

	<i>Anxiety</i>	<i>Sadness</i>	<i>Anger</i>
Social Interaction	 ***	 ***	 ***
#Followers		 ***	

- How individual differences are associated with the distress recovery process?

\*\*\*,  $p < .01$

\*\* ,  $p < .05$

\* ,  $p < .1$



# Summary

- We construct a computational focus group of Parisians and track their behavioral changes over time in the face of the Paris Attacks in Nov. 2015.
- Compared with traditional approaches, our framework is able to quickly evaluate the immediate emotional response and its recovery process.
- We discover the individual differences are associated with different immediate response as well as different recovery processes
- Social interactions alleviate the distress level while media exposure related to the attacks rises the level of distress.

# Future Work

- We plan to conduct different case studies under this framework to evaluate the impact of terrorist attacks as well as other types of traumatic events.
- We plan to explore the frameworks can study the impact beyond the emotions in the urban space, e.g., human mobility, livelihood.

# Thank you and Questions?

[xidao.wen@pitt.edu](mailto:xidao.wen@pitt.edu)

@XidaoWen

# Back-ups

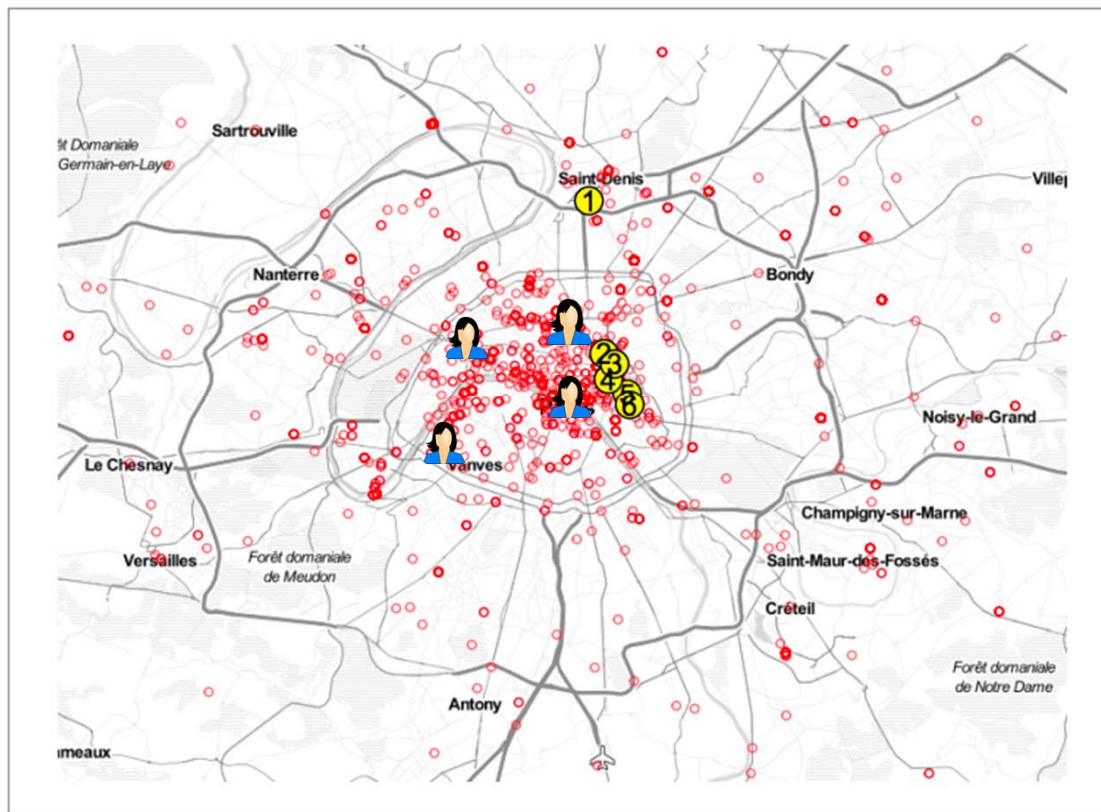
Table 1: Regression Results

	Linear Regression Models			Growth Mixture Models					
	(anx)	(sad)	(anger)	Intercept			Slope		
	(anx)	(sad)	(anger)	(anx)	(sad)	(anger)	(anx)	(sad)	(anger)
followers count	-.001	.002	-.003	.001	.009**	-.003	-.002	-.014**	.002
friends count	-.002	-.002	-.001	.000	.001	.001	-.003	-.004	-.006
gender male	-.01	-.01*	-.002	.000	-.009	-.002	-.005	.018	-.003
prior geographic distance	.000	-.002	.002	-.003	.007	-.007	.005	-.016*	.02**
post geographic distance	-.004	.004	-.004	.000	-.004	.000	-.003	.008	-.006
<i>after the attacks</i>	<i>aggregated measures</i>			<i>repeated measures</i>					
cognitive complexity	-.002	-.004	-.001				.002	.000	-.001
psychological distancing	-.01**	.001	.001				-.002	.000	-.003
media exposure	.01**	-.004	.01**				.016**	-.002	.013**
communication rate	-.001	-.004	.001				-.004**	-.007**	-.007**
Subjects	1,168	1,168	1,168	1,121	1,121	1,121	1,121	1,121	1,121

Note: the table lists the estimated coefficients.

\* p<.05; \*\* p<.01

- Independent Variables
  - **Geographic Proximity**
  - Media Exposure
  - Social Support
  - Gender



## Prior- and Post-Attack Geographic Proximity

Measured by the inverse of Alice's median distance from her geo-located tweets to the closest attack sites.

- Independent Variables
  - Geographic Proximity
  - **Media Exposure**
  - Social Support
  - Gender



Measured by the proportion of Alice's tweets contain hyperlinks and attack related keywords

- Independent Variables
  - Geographic Proximity
  - Media Exposure
  - **Social Support**
  - Gender



Measured by Follower/Followee size  
and Tendency of interacting with others