
Sentiment Analysis of Twitter Response to Major World Events

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Problem Description

What is the problem?

- Social media makes available unprecedented amounts of unstructured content concerning the sentiments and opinions of populations.
- How can we make sense of this?

Why is important?

- Understanding how the populations of different states react differently to events will help to increase understanding of cultural and political differences, and potentially aid in policy decisions and political campaigning.



Problem Description

Who cares about it?

- Users could include politicians and political activists.
 - Great utility to decision-makers and the authorities.

Why does it remain unsolved?

- The performance on social media data is still unsatisfactory due to the distinct data characteristics
 - Social media posts are always short and unstructured.
 - It is labor intensive and time consuming to obtain ground truth for training data.



Objectives

- Monitor the most talked about messages at any given time to chronicle the civilian response to major events.
- Reduce Dimensionality.
- Compare generated topics from different populations.
- Perform a visualization of the emotions obtained on a world map to understand the sentiments from different parts of the world.

Related Work

Hughes and Palen (2009)

- Surveyed the adoption and use of Twitter during mass convergence and emergency events.

Cheong and Lee (2011)

- Assigned responses into seven distinct categories: Fear/Anxiety, Shock, Response, Need for information and Updates, Threat Assessment, Casualties Assessment, and Response and Law Enforcement.

Jungherr (2009)

- Detailed the role of Twitter in social activism and looked into case studies whereby Twitter was an instrumental tool in disseminating information on terrorist attacks, political dissent, and acts of oppression.

Data-Extraction

- Paris Attack - Nov 12/13
- Tweets over the period of November 17, 2015 to November 26, 2015
- Divided our final data (60,998 tweets) into two subsets
 - Tweets from 39 major cities (4,673 tweets)
 - Tweets from around 1000 cities around the world (56,325 tweets)
- Data cleaning
 - Removed whitespace
 - Ignored case
 - Removed punctuation



Models

Latent Dirichlet Allocation (LDA)

- Unsupervised machine learning technique that identifies latent topic information.
- A member of a family of models known as probabilistic topic models.

Pachinko Allocation Model (PAM)

- Captures correlations using a Directed Acyclic Graph (DAG), where topic nodes occupy the interior levels and the leaves are words.

Approach

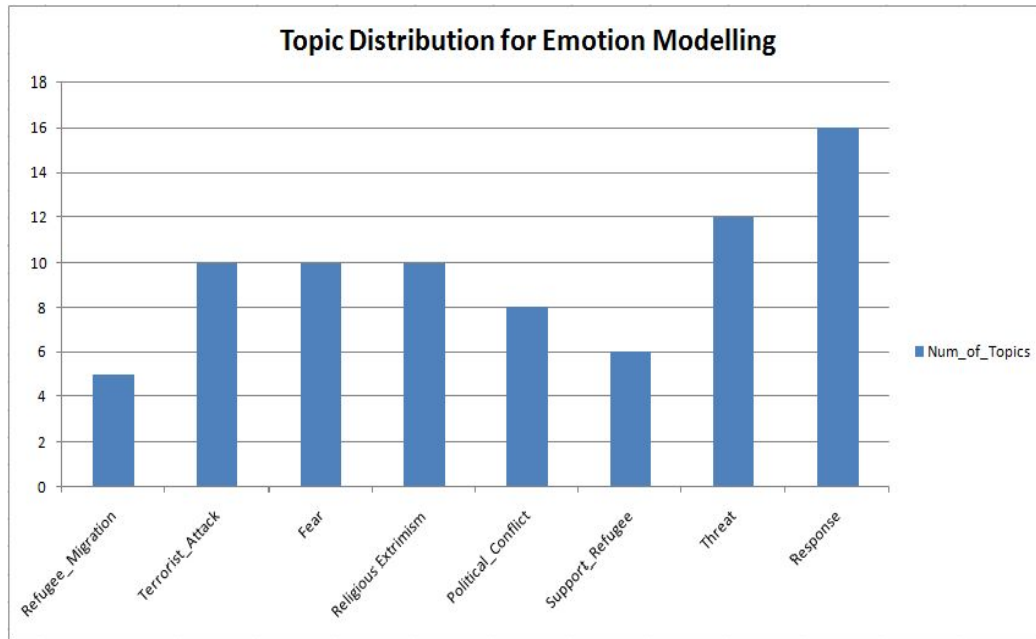
Analyses

After performing topic modeling on the corpus with a total topic count of 400, we manually went through all 400 generated topics and selected those that were coherent and related to one of our topics of interest.

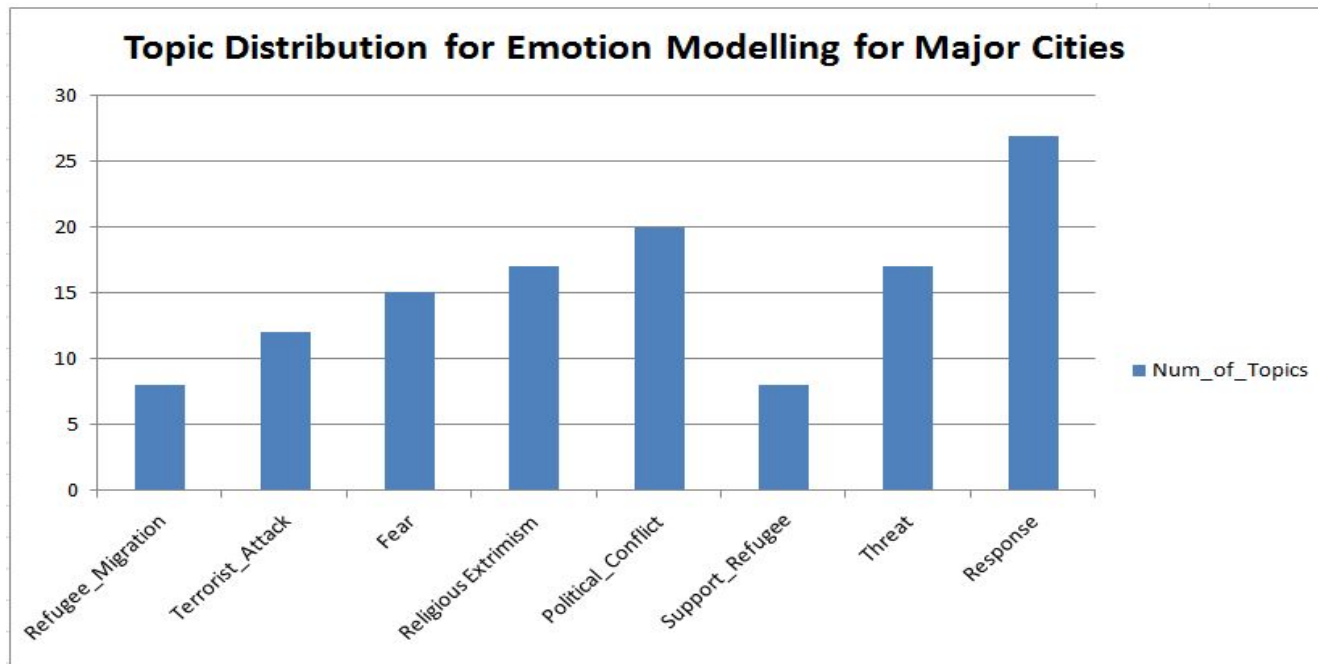
For Pachinko we had 200 sub-topics grouped into 20 super-topics.

<i>Fear</i>	Anxiety, Anxiousness, Catastrophic, Concern, Disaster, Fear, Insecure, Panic, Scared, Terror, Trouble, Warning, Worry
<i>Political Conflict</i>	Assad, Syria, Russia, Turkey, Policy, EU, Emergency, Embargo, Sanction, Xenophobia, France, USA
<i>Refugee Migration</i>	Open, Border, Ship, Boat, Refugees, Racist, Child, Women, Sleep, Food, Transport
<i>Religious Extremism</i>	Bigotry, Shame, Muslim, Execute, Trust, Intolerance, Hindu, Christian, Islam, Hate, Foul Play
<i>Response</i>	Breaking News, Call, Incident, Phone, Report, Situation, Unconfirmed, Act, Asap, Escape, Evacuate, Flee, Help, Hide, Run
<i>Support Refugee</i>	Welcome, Refugee, Commitment, Homeless, Support, Obama, Republican, Asylum, Trump
<i>Terrorist Attack</i>	Attack, Bomb, Bullet, Collapse, Crash, Explosion, Fire, Gun, Hijack, Hit, Hostage, Plane, Responsibility, Rifle, Shoot, Struck, Suicide, Terrorist
<i>Threat</i>	Threats, Accident, Shock, Aback, Floor, God, Bless, Omg, Shock, Stun, Sudden

Larger Sample- This process resulted in a total of 77 relevant topics out of 400. Then, these topics were manually classified into one of our eight topic groups.

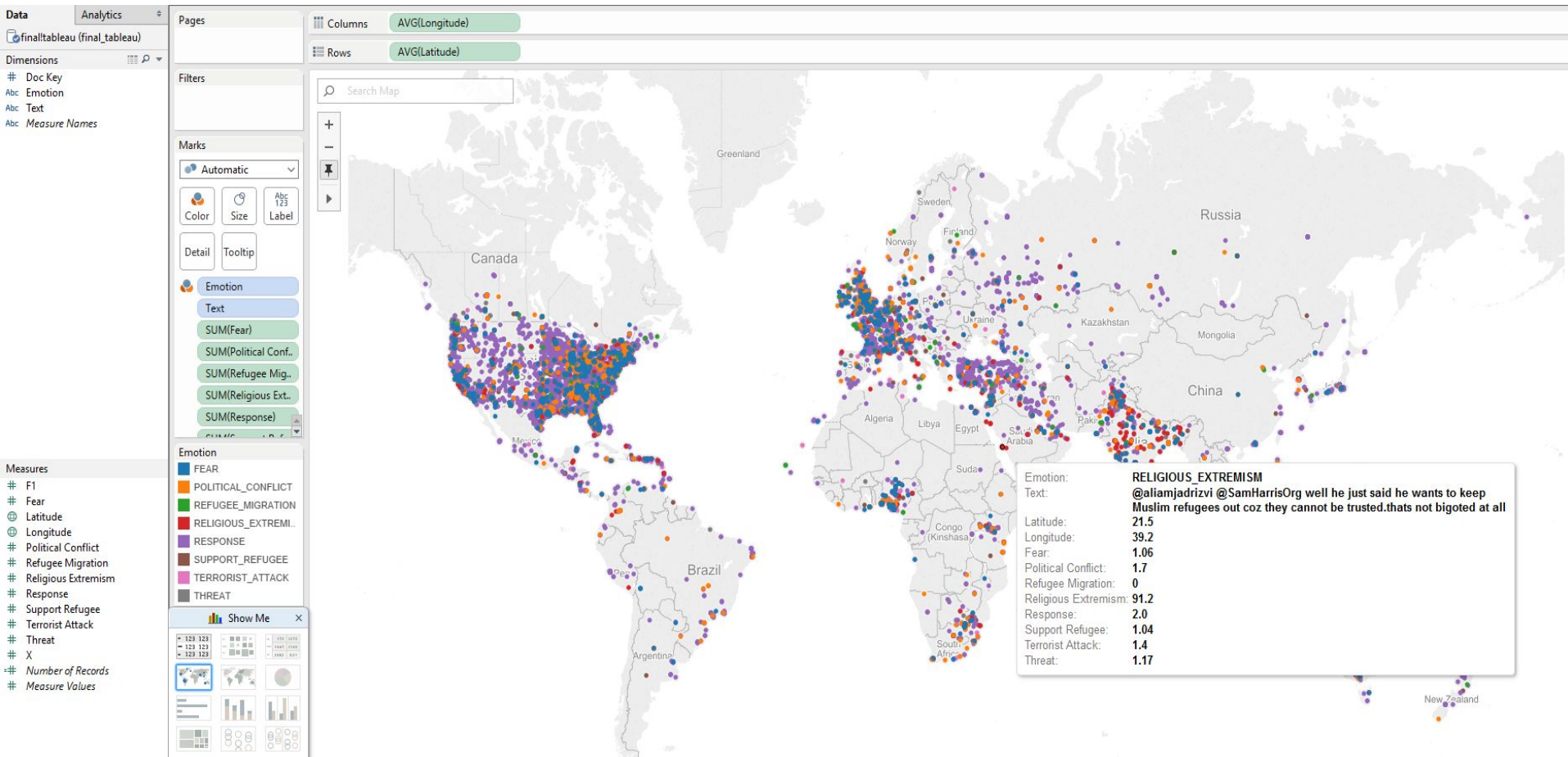


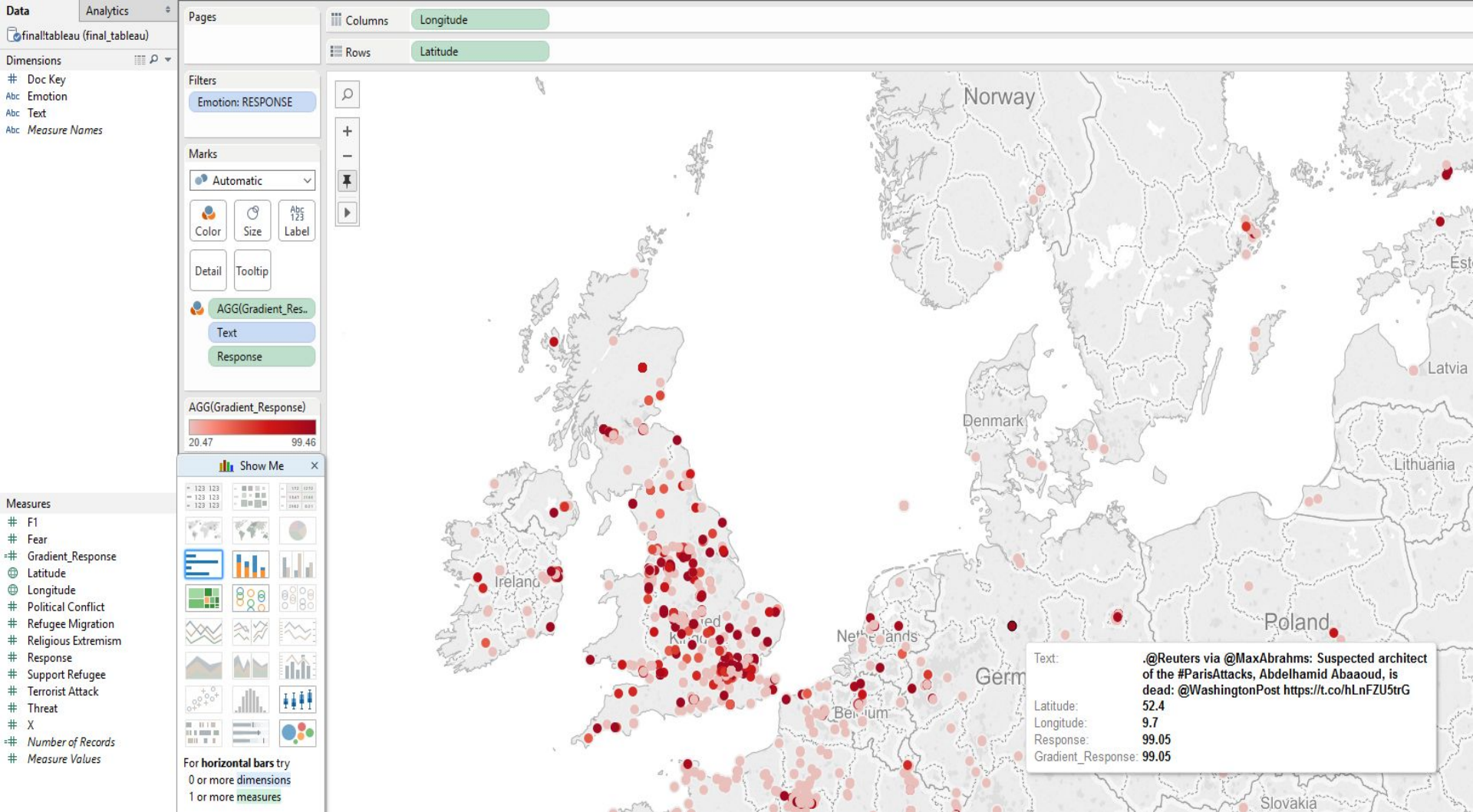
Topic Distribution for Major Cities



Total of
124 topics

Results





Marks

Automatic

Color Size Label

Detail Tooltip

Fear

Political Conflict

Religious Extremism

Response

Support Refugee

Terrorist Attack

Threat

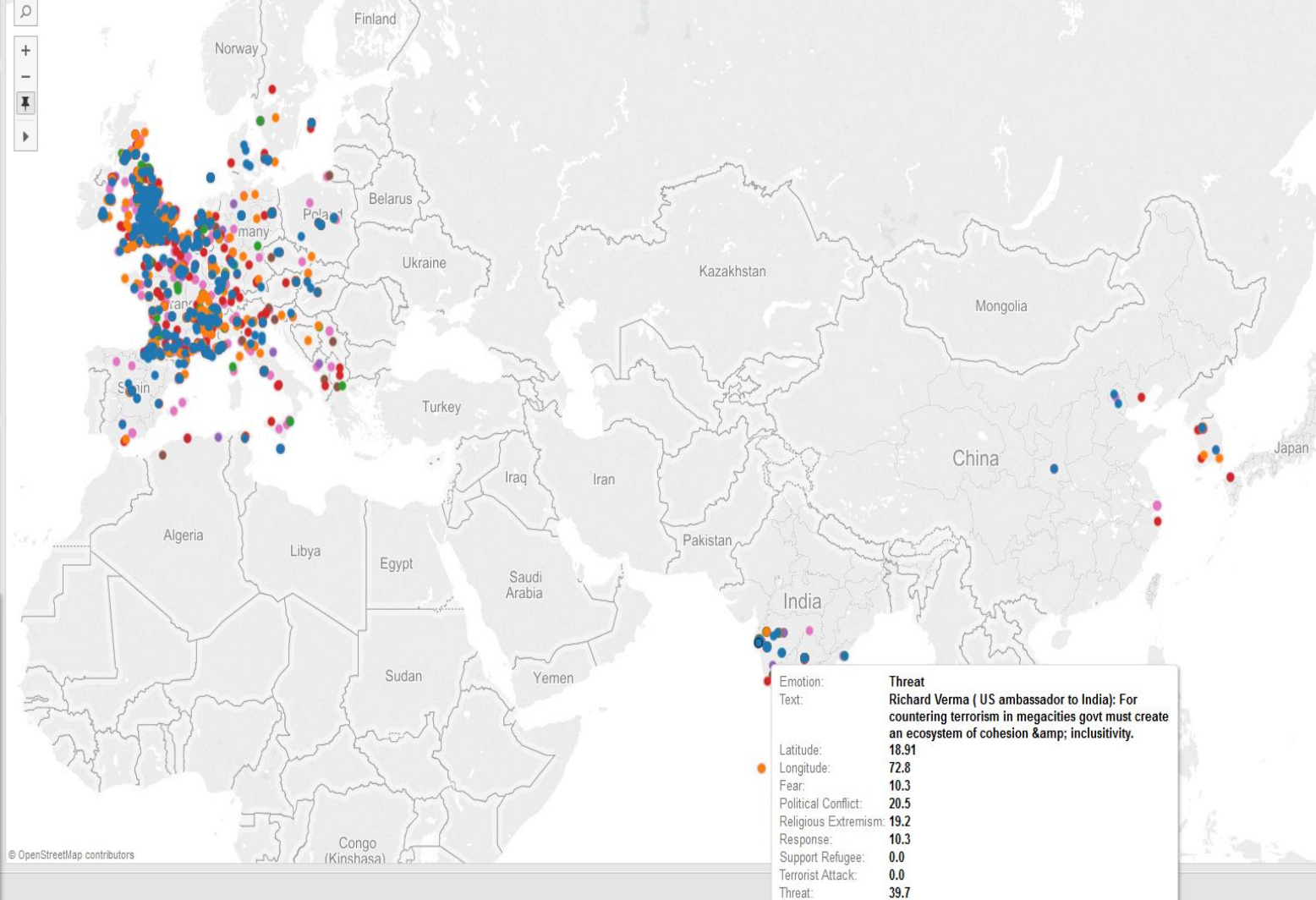
Measures

- # F1
- # Fear
- # Latitude
- # Longitude
- # Political Conflict
- # Religious Extremism
- # Response
- # Support Refugee
- # Terrorist Attack
- # Threat
- # Number of Records
- # Measure Values

Show Me

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Data Source Sheet 1



Limitations

- Tweets need to be Geo-Tagged.
- Contents written in different languages but in the same (Latin) Alphabet.

Evaluation

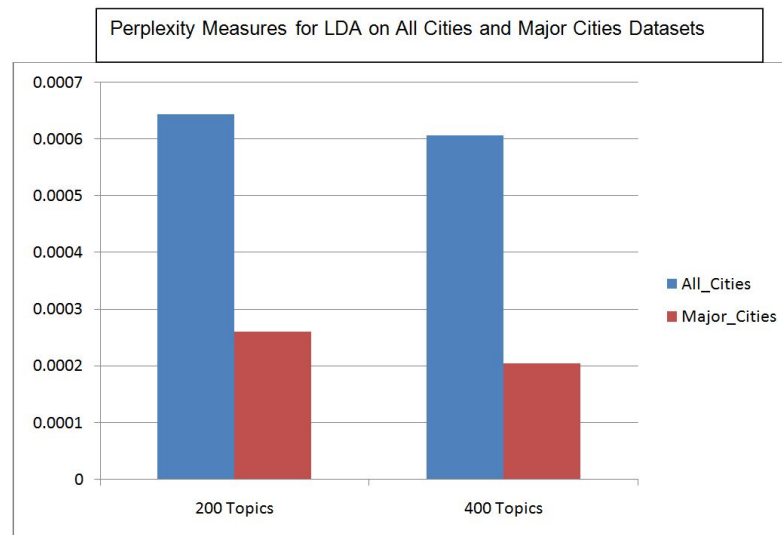
As there are distinct differences in super-topics discussed by different regions, we consider our project to be a success.

LDA Emotions:

- UK: Political Conflict
- Middle East: Religious Extremism
- Eastern Europe: Refugee migration

Pachinko Allocation Emotions:

- UK : Political Conflict and Fear
- India: Threat



Conclusion and Recommendations

- Distinct difference in Opinion/Emotion in different regions of the world.
 - Topic modelling can provide distinction of tweets across geographic areas
- Varying Gradient of an Emotion in a Region.
- Expand work to Languages other than English.
- Scalability of Pachinko.
- Spatial clustering.
- Human-in-the-loop validation of topics - AWS Mechanical Turk?

