

# Spatial Analysis of Emotional Language on Twitter in the U.S.

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## Introduction

To understand the relationship between language use and thought has long been an important and vibrant area of research in social sciences, especially psychology. Yet, studying language can traditionally require time-intensive qualitative approaches, often with only a small number of respondents. Computational linguistics offers techniques to study language use at large scale, requiring substantially less time, money, and other resources (Iliev et al., 2015). No longer constrained by results based on small samples of individuals, language offers many interesting opportunities to directly study people’s thoughts and emotions (Lazer et al., 2009). Yet as data move from gigabytes to terabytes to petabytes, finding a reliable interpretable signal becomes more of a process of searching for a needle in a hay field. Theories are needed to meaningfully interpret data, and psychologists have developed such theories over decades. Incremental benefit can come by collaborating with experts from other fields, including quantitative psychologists, methodologists, statisticians, economists, political scientists, health experts, and educators.

One of the most important lines of research in psychology and language has focused on representation of human emotions in language. An emotion is a complex psychological state that consists of three distinct components: *a subjective experience*, *a physiological response*, and *a behavioral or expressive response*. Only very recently, computational social scientists have started to look at the representations of different emotions in language. Computer scientists have also started to examine affective processes in textual data, often labeled as sentiment analysis, defined as the process of computationally identifying and categorizing opinions expressed in a piece of text, especially in order to determine whether the writer’s attitude towards a particular topic, product, etc., is positive, negative, or neutral. To do such analyses, scholars from different fields have relied on large-scale corpora (sometimes referred to as big data) from different sources. Before any analyses can be conducted, data must be obtained. Careful consideration should be given toward which data will be most appropriate for the question under investigation, and if informative datasets are accessible (Kern et al., 2016). As Borgman (2015) has noted, “having the right data is usually better than having more data” (p. 4). Some shared data resources exist. Social media platforms have provided psychologists and computer scientists with a rich, naturally occurring environment to investigate human behavior at scale (Serrano-Guerrero et al., 2015).

Twitter as an important social media platform for people, across cultures, to publically express their opinions and feelings about their community and their private life, has attracted increasing attention with millions of active members in different countries (Li et al., 2013). A number of empirical studies have been published on sentiment analysis on Twitter (Poria et al., 2014). Methods for sentiment classification have been developed ranging from simple text mining to advanced symbol and feature recognition to a sentiment and subjective analysis (Oscar et al., 2017) and machine learning or lexicon-based approaches to more advanced hybrid methods (Serrano-Guerrero et al., 2015) and from sentiment orientation with only two modes (i.e., negative versus positive) to coarse measurement scale and more nuanced classifications (Fink et al., 2011). Yet, few sentiment analysis studies have utilized a geospatial and/or temporal computational methods.

A growing number of language studies on Twitter are trying to incorporate geospatial methods into their sentiment analyses. Medhat et al. (2014) categorized sentiment analyses into two groups: machine learning and lexicon-based approaches. Broadly, machine-learning methods are used to automatically identify sentiment polarity patterns in large corpora in order to learn mass opinions or emotions in textual data. A variety of algorithms have been developed (e.g., Rushdi Saleh et al., 2011) for this purpose. Most algorithms fall into

the category of supervised machine learning. Lexicon-based approaches focus on measuring subjectivity and opinions in texts using Semantic orientation (SO), which capture orientations of sentiments (i.e., negative or positive) and strengths or degrees of orientation (Taboada et al. 2011). Sentiment lexicons are the key for this type of methods. For example, Paltoglou and Thelwall (2012) proposed a lexicon-based approach to identify whether a text conveys negative or positive attitudes and to estimate the level of emotional intensity of a text in social media and microblogging environments.

More recently, Eichstaedt and colleagues (2015) collected tweets from across the United States, determined tweets’ counties of origin, and derived values for a number of language variables (e.g., the relative frequencies with which people expressed anger or engagement) for each unit of analysis (i.e., county). These authors correlated these county-level language measures with county-level age-adjusted heart disease mortality rates obtained from independent health organizations (i.e., CDC). All procedures of these authors were approved by the University of Pennsylvania Institutional Review Board. In addition, they provided access to their data on Open Science Framework (OSF).

As mentioned before, Tweets messages on Twitter containing information about emotions, thoughts, behaviors, and other personally salient information. In 2009 and 2010, Twitter made a 10% random sample of tweets (the “Garden Hose”) available for researchers through direct access to its servers. Eichstaedt et al. (2015) obtained a sample of 826 million tweets collected between June 2009 and March 2010. Many Twitter users self-reported their locations in their user profiles, and these authors used this information to map tweets to counties. This resulted in 148 million county-mapped tweets across 1,347 counties. An automatic process was used to extract the relative frequency of words and n-grams for every county. For example, the relative frequency of the word hate ranged from 0.009% to 0.139% across counties. Then they derived two types of language-use variables from counties’ relative word-usage frequencies: variables based on (a) dictionaries and (b) topics. Dictionary-based variables were relative frequencies of psychologically related words from predetermined dictionaries (e.g., positive-emotion words accounted for 4.6% of all words in a county on average). Topic-based variables were the relative usage of 2,000 automatically created topics, which are clusters of semantically related words that can be thought of as latent factors. These authors used pre-established dictionaries for anger, anxiety, positive and negative emotions, positive and negative social relationships, and engagement and disengagement (Pennebaker et al., 2007; Schwartz et al., 2013). Topics had previously been automatically derived (Schwartz et al., 2013).

In this project, I used the data provided by Eichstaedt et al. (2015) as outlined above. The lexicon-based frequencies were used in this project. Latent factors (i.e., topic models) were not used for simplicity. I was particularly interested in emotion words and their geospatial distribution in the United States in over 1000 counties. The dictionaries that were used in the published paper are presented in Table 1. I used a number of *Tidyverse* packages to compute relative emotions in language use, merge the datasets from the paper and the *ggplot2* package, and visualize the distribution of eight psychologically important emotional constructs (i.e., *anger*, *anxiety*, *negative relationships*, *positive relationships*, *negative emotion words*, *positive emotions words*, *engagement*, and *disengagement*). These analyses are in line with my personal line of research.

```
## Warning: package 'knitr' was built under R version 3.4.3
## Parsed with column specification:
## cols(
##   Dictionary = col_character(),
##   `Top Ten Dictionary Words by Frequency` = col_character()
## )
```

Table 1: Emotion Categories and Their Sample Words

Dictionary	Top Ten Dictionary Words by Frequency
Anger	shit f*** hate damn btch hell f**ing mad stupid b*tches
Negative Relationships	hate alone jealous blame evil rude lonely independent hated ban
Negative Emotion	sorry mad sad scared p*ssed crying horrible afraid terrible upset
Disengagement	tired bored sleepy lazy blah meh exhausted yawn distracted boredom

Dictionary	Top Ten Dictionary Words by Frequency
Anxiety	crazy pressure worry scared awkward scary fear doubt horrible afraid
Positive Relationships	love home friends friend team social welcome together kind dear
Positive Emotion	great happy cool awesome amazing glad excited super enjoy wonderful
Engagement	learn interesting awake interested alive learning creative alert involved careful

## Data Manipulation

```
##loading libraries
library(dplyr)

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##   filter, lag

## The following objects are masked from 'package:base':
##
##   intersect, setdiff, setequal, union

library(readr)
library(ggplot2)
library(ggmap)
##reading the dataset
cat = read_csv("~/Desktop/categorized dictionary with city name.csv")

## Parsed with column specification:
## cols(
##   group_id = col_integer(),
##   feat = col_character(),
##   city_name = col_character(),
##   lex_cat = col_character()
## )

##writing the data on a CSV format
write_csv(cat, "cat.csv")

#city and category
citycat = cat%>%
  group_by(city_name, lex_cat)%>%
  summarize(n())

#changing column names
citycat$city = citycat$city_name
citycat$emotion = citycat$lex_cat
citycat$word = citycat$n`

citycat = citycat%>%
  dplyr::select(c("city", "emotion", "word"))

## Adding missing grouping variables: `city_name`
```

```

city_words = citycat%>%
  group_by(city)%>%
  summarise(sum(word))

city_words_emotions = full_join(citycat, city_words, by = "city")

city_words_emotions = mutate(city_words_emotions, rel.emotion = word/sum(word))

## Warning: package 'bindrcpp' was built under R version 3.4.4

##different emotions
#anger
city_words_emotions_ANGER = filter(city_words_emotions, emotion == "ANGER")
#anxiety
city_words_emotions_ANXIETY = filter(city_words_emotions, emotion == "ANX")
#positive emotions
city_words_emotions_POSEMO = filter(city_words_emotions, emotion == "E+")
#negative emotions
city_words_emotions_NEGEMO = filter(city_words_emotions, emotion == "E-")
#engagment
city_words_emotions_ENGAGE = filter(city_words_emotions, emotion == "P+")
#disengagement
city_words_emotions_DISENGAGE = filter(city_words_emotions, emotion == "P-")
#positive relationships
city_words_emotions_POSREL = filter(city_words_emotions, emotion == "R+")
#negative relationships
city_words_emotions_NEGREL = filter(city_words_emotions, emotion == "R-")

```

## Plots

The following code provides merging the datasets and visualizations for the 8 emotional constructs.

```

#getting map data

USmap = map_data("county")

## Warning: package 'maps' was built under R version 3.4.4

USmap$city = USmap$subregion

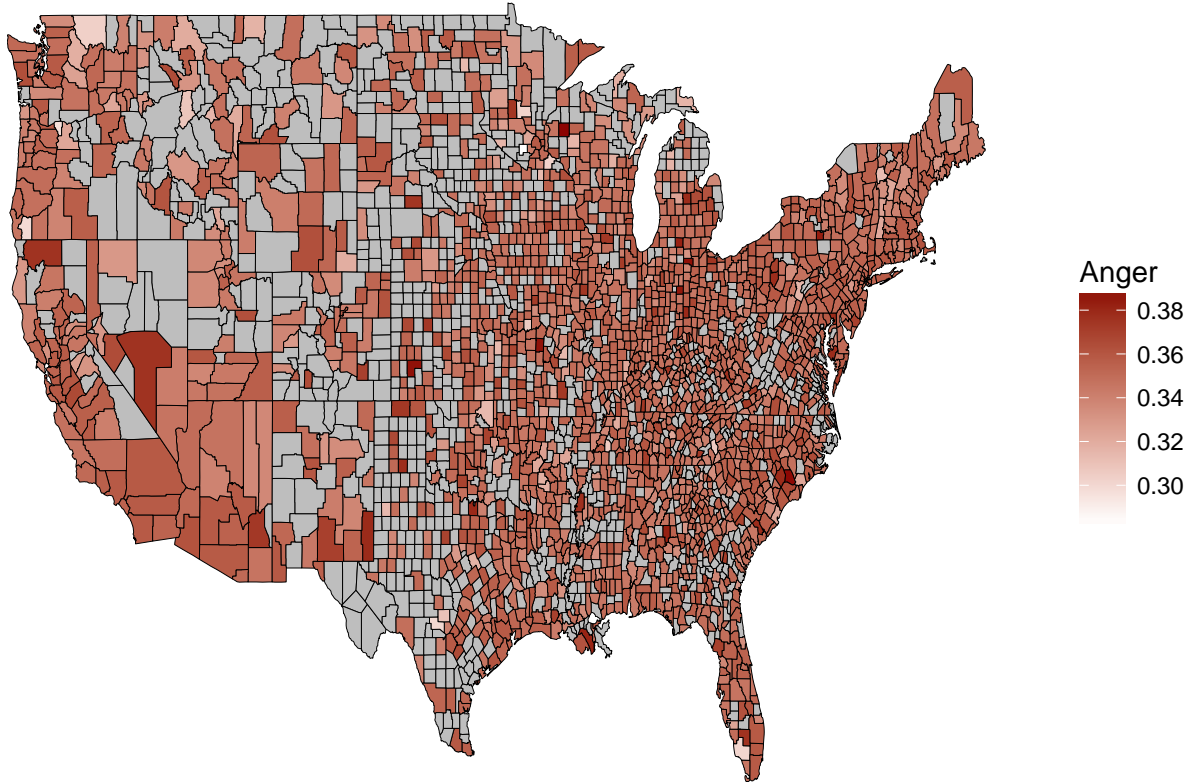
#merging

data.ANGER = full_join(USmap, city_words_emotions_ANGER, by = "city")
data.ANX = full_join(USmap, city_words_emotions_ANXIETY, by = "city")
data.POSEMO = full_join(USmap, city_words_emotions_POSEMO, by = "city")
data.NEGEMO = full_join(USmap, city_words_emotions_NEGEMO, by = "city")
data.ENGAGE = full_join(USmap, city_words_emotions_ENGAGE, by = "city")
data.DISENGAGE = full_join(USmap, city_words_emotions_DISENGAGE, by = "city")
data.POSREL = full_join(USmap, city_words_emotions_POSREL, by = "city")
data.NEGREL = full_join(USmap, city_words_emotions_NEGREL, by = "city")

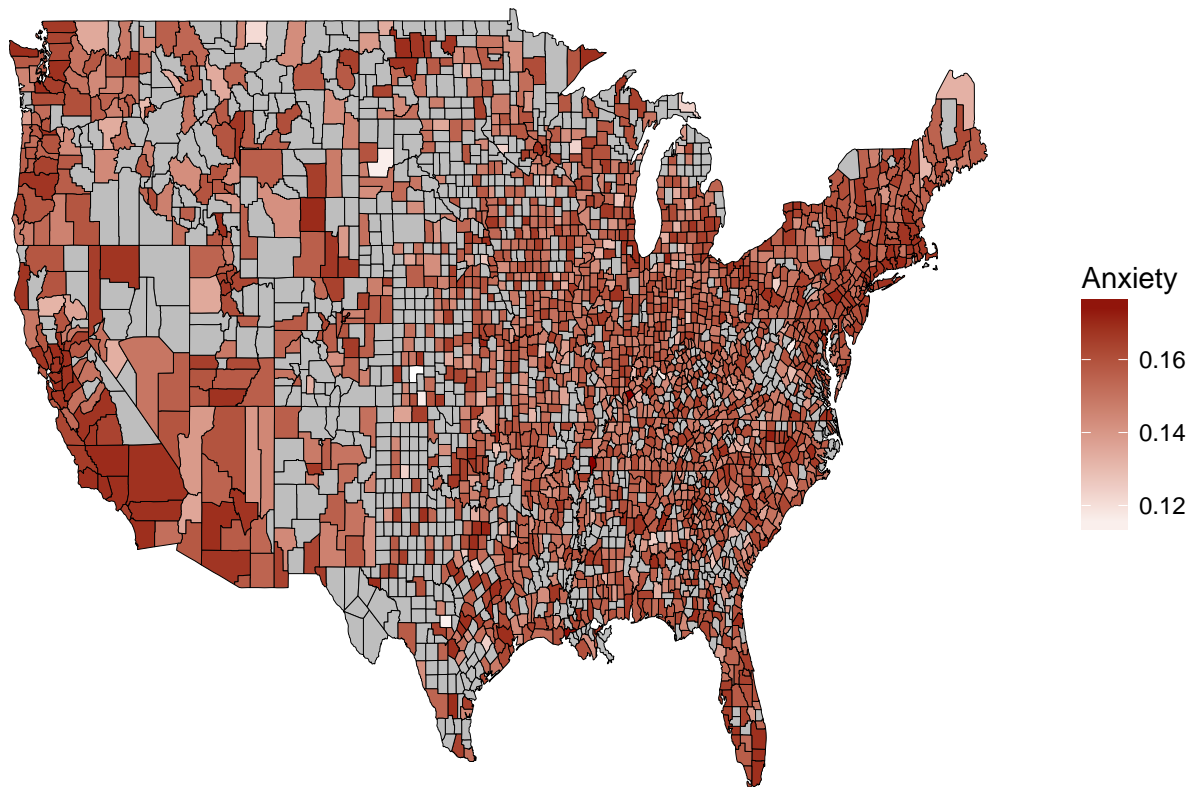
## Plots
#anger

```

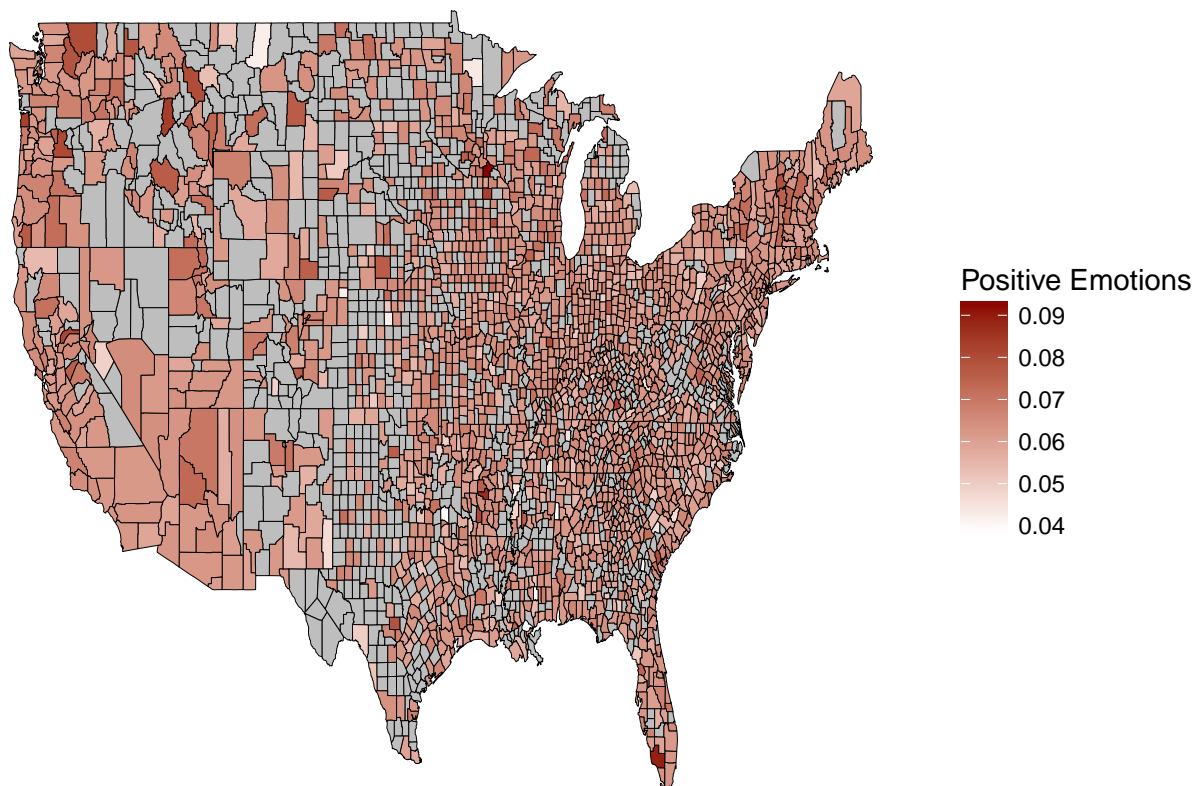
```
ggplot(data.ANGER, aes(x = long, y = lat, group = group, fill = rel.emotion))+
  geom_polygon(color = "black", size = .06)+
  scale_fill_gradient(low = "white", high = "darkred", na.value = "gray",
                     guide_legend("Anger"))+
  theme_void()
```



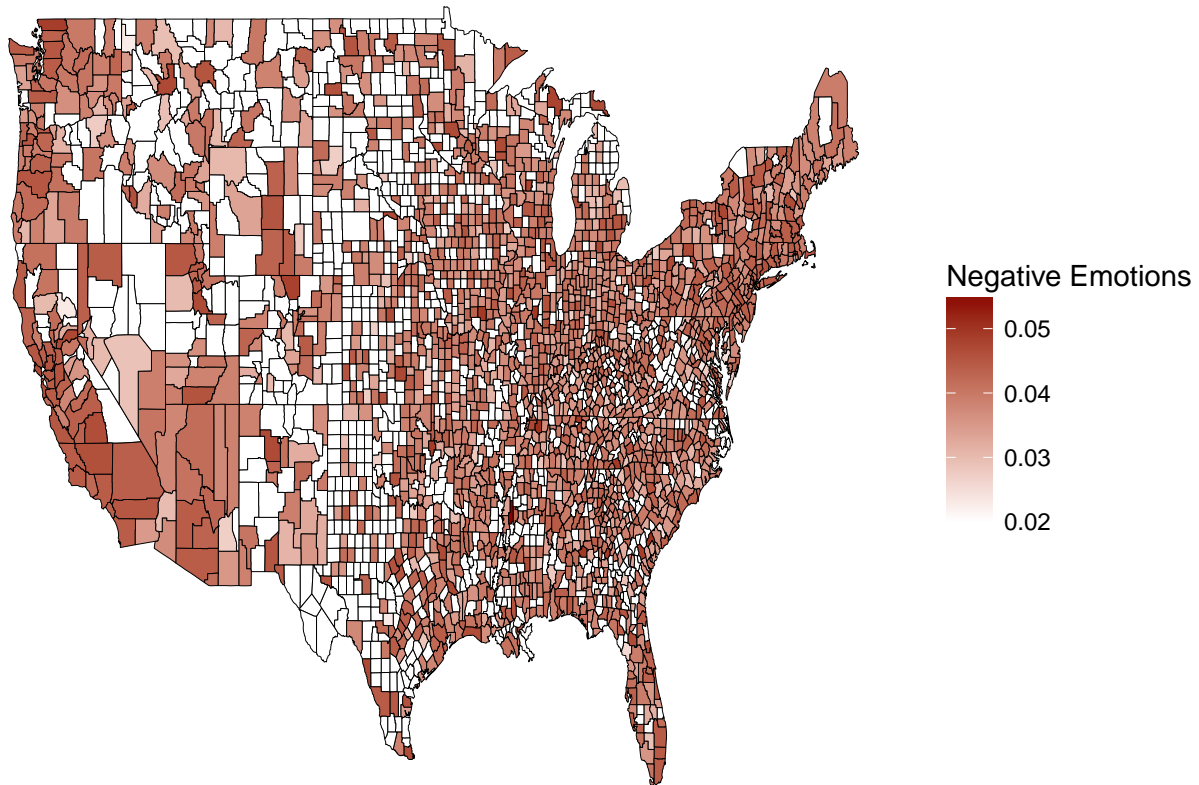
```
#anxiety
ggplot(data.ANX, aes(x = long, y = lat, group = group, fill = rel.emotion))+
  geom_polygon(color = "black", size = .06)+
  scale_fill_gradient(low = "white", high = "darkred", na.value = "gray",
                     guide_legend("Anxiety"))+
  theme_void()
```



```
#positive emotions  
ggplot(data.POSEMO, aes(x = long, y = lat, group = group, fill = rel.emotion))+  
  geom_polygon(color = "black", size = .06)+  
  scale_fill_gradient(low = "white", high = "darkred", na.value = "gray",  
    guide_legend("Positive Emotions"))+  
  theme_void()
```

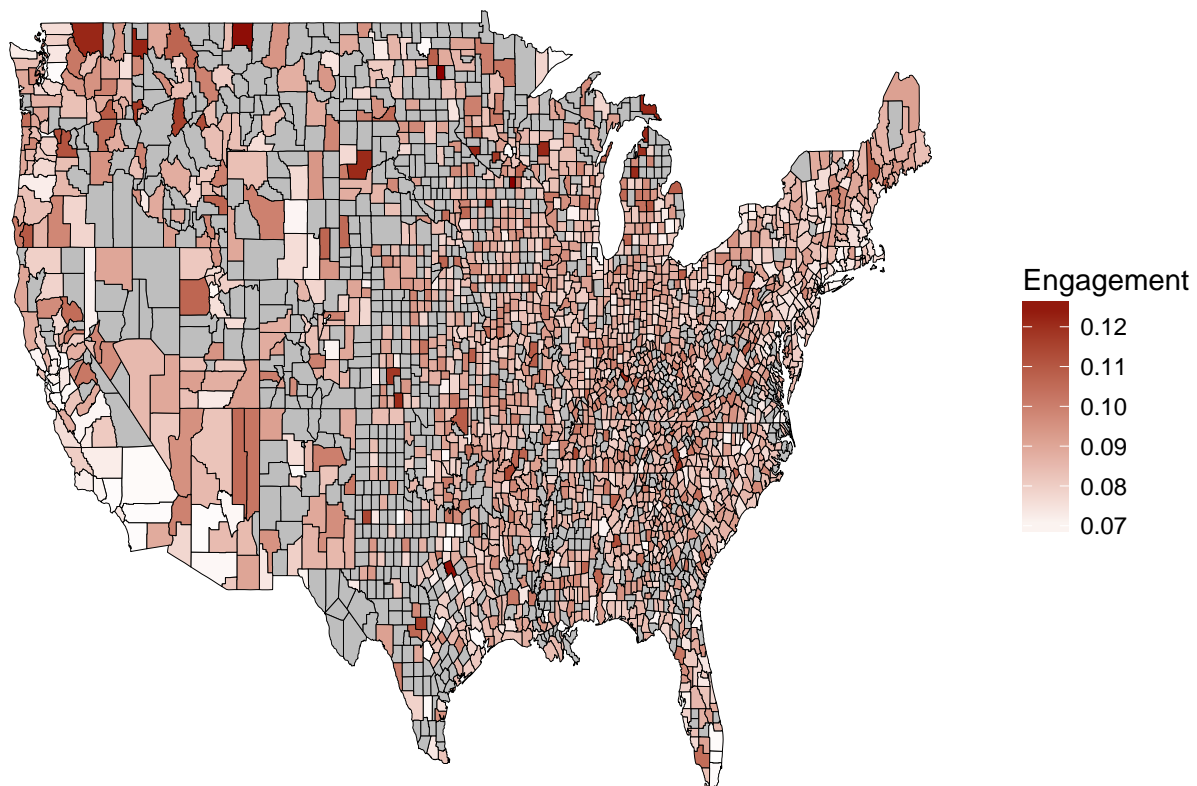


```
#negative emotions
ggplot(data.NEGEMO, aes(x = long, y = lat, group = group, fill = rel.emotion))+
  geom_polygon(color = "black", size = .06)+
  scale_fill_gradient(low = "white", high = "darkred", na.value = "white",
    guide_legend("Negative Emotions"))+
  theme_void()
```

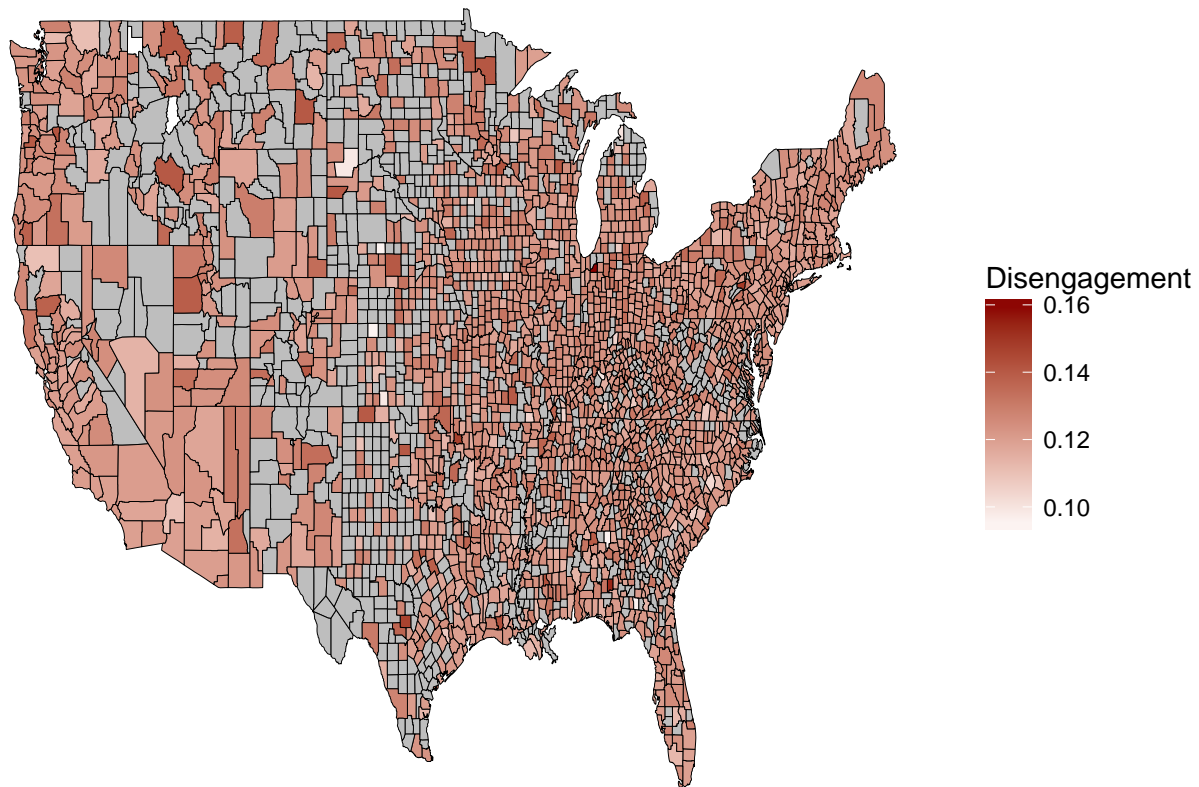


```
#engagment  
ggplot(data.ENGAGE, aes(x = long, y = lat, group = group, fill = rel.emotion))+  
  geom_polygon(color = "black", size = .06)+  
  scale_fill_gradient(low = "white", high = "darkred", na.value = "gray",  
    guide_legend("Engagement"))+  
  theme_void()
```

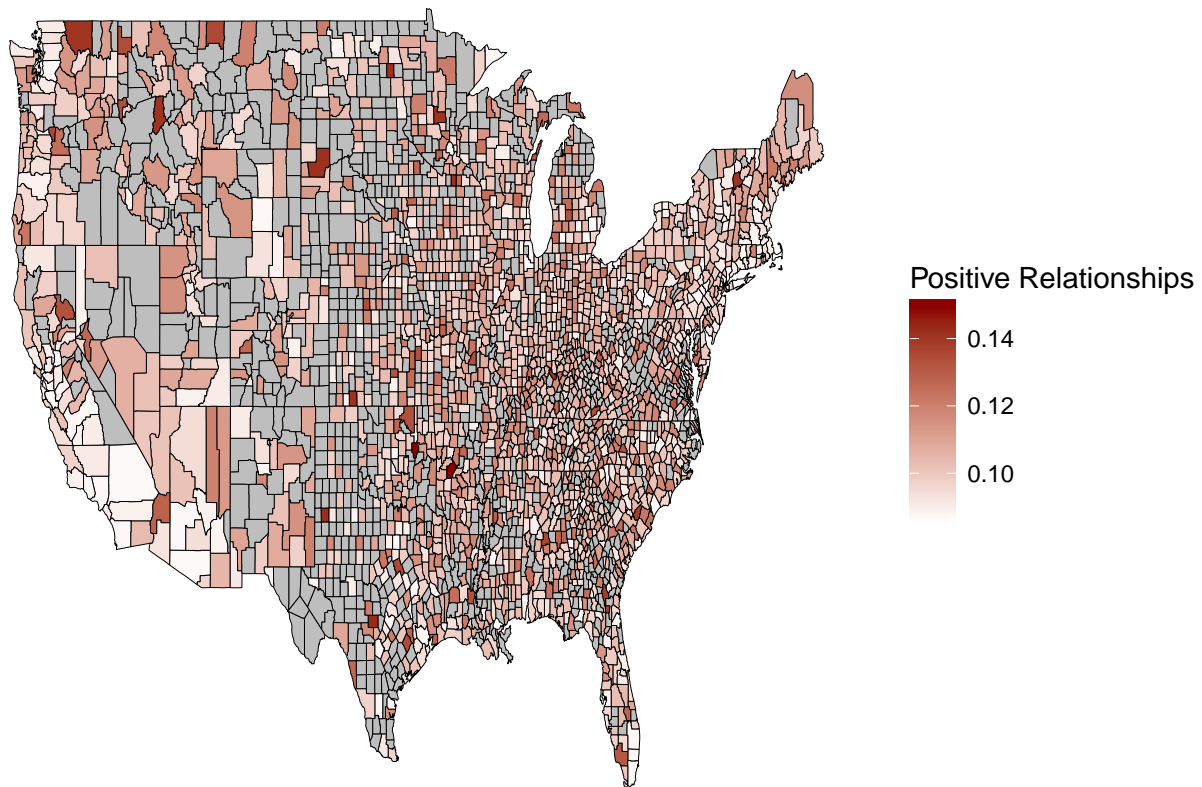




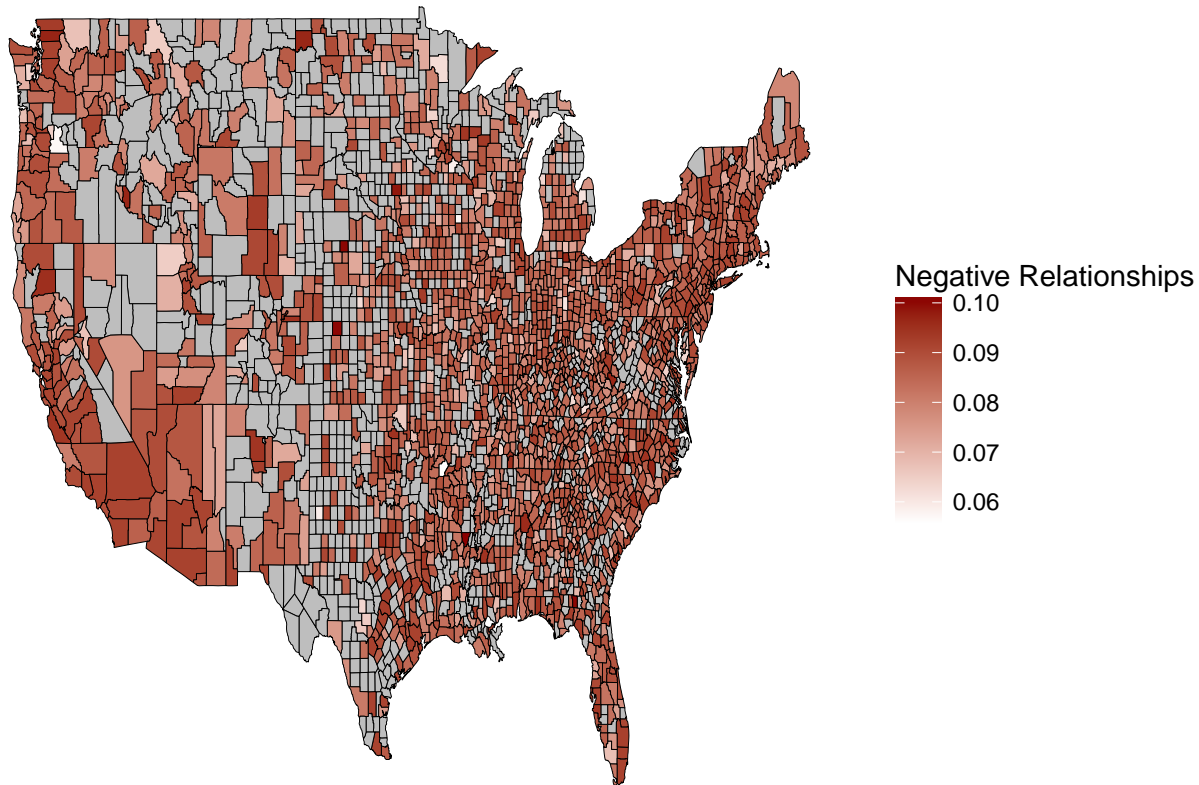
```
#disengagement  
ggplot(data.DISENGAGE, aes(x = long, y = lat, group = group, fill = rel.emotion))+  
  geom_polygon(color = "black", size = .06)+  
  scale_fill_gradient(low = "white", high = "darkred", na.value = "gray",  
                     guide_legend("Disengagement"))+  
  theme_void()
```



```
#positive relationships
ggplot(data.POSREL, aes(x = long, y = lat, group = group, fill = rel.emotion))+
  geom_polygon(color = "black", size = .06)+
  scale_fill_gradient(low = "white", high = "darkred", na.value = "gray",
    guide_legend("Positive Relationships"))+
  theme_void()
```



```
#negative relationships
ggplot(data.NEGREL, aes(x = long, y = lat, group = group, fill = rel.emotion))+
  geom_polygon(color = "black", size = .06)+
  scale_fill_gradient(low = "white", high = "darkred", na.value = "gray",
    guide_legend("Negative Relationships"))+
  theme_void()
```



## Conclusion

From a psychological standpoint, geospatial analyses provide a unique and new perspective to examine the distribution of psychologically relevant variables in geographic regions. Using traditional methods and small samples in psychology, it was almost impossible to investigate large-scale variations in emotions across the states, however, using more advanced methods it has become feasible to do so. In this study, I examined geospatial distribution of eight emotion-related constructs identified by previous research across the U.S. Although in many data science or business courses, such visualizations are used for presentation of a problem or future recommendations, psychologists can use such visualizations to combine these new findings with previous literature. For example, it can be interesting to see how county-level health outcomes are associated with county-level emotions, as measured using social media analyses. In addition, many psychological theories are geospatial in nature. For example, there are multiple evolutionary theories about the origins of multiple emotions (e.g., disgust, anger, happiness) that link environmental factors and human cognitive factors. It is recommended for future research to examine the distribution of such emotional constructs across different geographical regions.

As mentioned before, these analyses are consistent with my personal line of research at Computational Social Science Lab (CSSL) at USC. I have used geospatial analysis in my most recent work which has been accepted for presentation at the annual convention of the Association for Psychological Science in San Francisco on May 26th, 2018. I hope to incorporate these methods (e.g., text analytics, geospatial analysis, time series) further in my future research.

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