

The Cuban Thaw Visualization Project

[Website](#) & Process Book

Jerry Castro & Ivan Lima

CS 171, Harvard University

May 4th, 2015

# **Table of Contents**

**Project Pivot**

**Overview and Motivation**

**Related Work**

**Questions**

**Data**

**Exploratoration**

**Design Evolution**

**Implementation**

**Evaluation**

## **Project Pivot**

Our CS171 Final Project took a major pivot from its initial proposal but we strongly believe it more than makes up for it with technical rigor. Before diving more deeply into our final project, we think it is important to briefly explain why we pivoted.

### **Why the Pivot?**

We initially proposed a thorough and rigorous visualization with four orthogonal views, each with several relevant filters, however our premier feature was a US map color coded based on a semantic analysis of the data that would determine whether or not a tweet was for or against the Cuban Thaw. Our TF was concerned that the project was too ambitious and that it might not be possible for us to complete this in time but In fact, that was not the issue. On a technical level, there was sufficient time to do everything we wanted to do.

Rather, as we got deeper into the semantic analysis aspect of the project towards the end of second week, it became apparent that the technology currently available could not provide us with highly reliable sentiment data without extensive optimizations that included custom dictionaries, grammars, and objects of speech. These were considerations that were beyond the time we had available so a change was required.

It must be noted though that this is not something we could have predicted in advance. Twitter's terms of service restricted us to downloading only 100,000 tweets per day, so the full dataset required 10 days to obtain. Furthermore, though our semantic analysis platform was extremely advanced and fully capable of analyzing tweets, it was also extremely costly. The cheapest option was \$999 per month. So we had to apply for academic access. It took sometime to get approval but ultimately the relatively small number of academic credits we were granted meant a true test of viability would have to wait until a proper, representative sample from the full dataset could be obtained.

## Overview and Motivation

*Our projects primary goal is to visualize the Cuban Thaw through a massive dataset of tweets animated and projected with high velocity onto both a map of the world and a of the United States.*

Hours of attempting to find an event in the Twitter era that we deemed historic and that would have an appropriate sample size of tweets brought us to the realization that the perfect topic was actually very recent. The restoration of diplomatic relations between the United States and Cuba on December 17, 2014.

This historic warming of relations between the US and Cuba was a monumental shift in foreign policy between two countries stuck in a bitter cold war for half of a century. The negotiations, surprisingly brokered by Pope Francis, made news on December 17th, 2014 and instantly captured everyone's attention. Republicans, Democrats, and politicians from around the world immediately put out statements to the media. Some were furious, others supportive. Many were cautious. Reports of the "Cuban Thaw" were all over the news. Footage from Miami, a heavily Cuban city, showed angry protesters in the streets holding up signs that said things like "This is treason" or "Obama is a traitor".

A pattern quickly emerged that continued throughout the day. The loudest opinions that were repeated over and over throughout the media, belonged to people in middle age and old age who still vividly remember the Cold War and the Soviet Union and the constant threat of nuclear war. Some of those Miami protesters lived in Cuba during the revolution that brought Communism to the country and destroyed countless families.

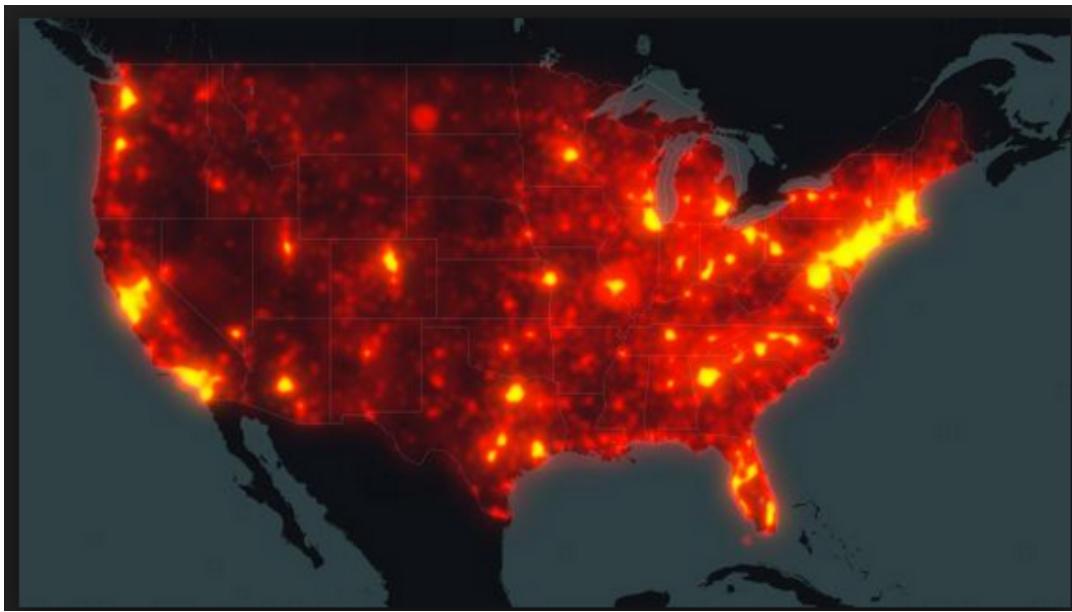
But it has been nearly 25 years since the end of the Cold War. Most American young adults today only know about Fidel Castro and the Soviet Union from history books, that is, if they know about them at all. Political scientists agree that they really aren't sure

how how this group of millions, the so called “millennials”, feel about the embargo. Of course they don’t. The answer is on Twitter, hidden inside a million tweets.

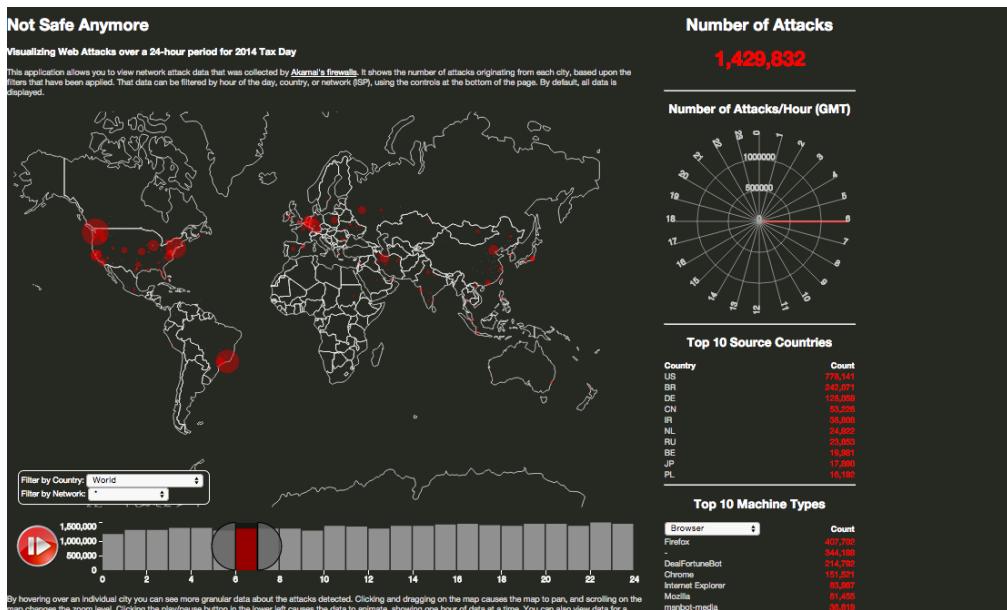
## Related Work

When we first started looking for a dataset to use for our project we struggled to find one that caught our attention. One night while browsing the web I stumbled on something both fascinating and heartbreaking. Wikileaks had released 500,000 pager intercepts from the day of 9/11. They showed reactions from that day in 5 minute intervals through peoples communications with their friends and family.

We ultimately decided that 9/11 was too dark and painful of a topic we realized that it was a good jumping off point for discovering a different topic. We were both intrigued by the idea of visualizing high volume social communication during a single major event. While it didn't exist during 9/11, we realized that twitter was the perfect medium for finding such data. Looking through hundreds of thousands of thousands of tweets on a single event, one is sure to find fascinating trends. During our search, the images below also served as inspiration.



*This was our mental image of what graphing the Cuban Thaw tweets might look like.*



*This website gave us some general ideas about actual the implementation and layouts.*

## Questions

### 4/04/15, Project Starts

- Can we gauge public opinion of The Cuban Thaw through tweets?
- Do the opinions of Millennials match the political tendencies of the state where they are from?
- How do Young Cuban Americans really feel about the policy?
- How do the 2016 Presidential candidates feel about the Thaw?
- How do members of Congress feel about the Thaw?

### 4/18/15, Midpoint

- Can we gauge public opinion of The Cuban Thaw through tweets?
- How does tweet volume vary across the US?
- What proportion of Republicans in favor of the Thaw come from states with large agricultural industries? (Cuba imports 80% of its food)
- How do the 2016 Presidential candidates feel about the Thaw?
- How do members of Congress feel about the Thaw?
- Do the opinions of Millennials match the political tendencies of the state where they are from?

### 5/05/15, Project Due

- How does tweet volume vary across the World & the US?
- How important did the world find the event?
- Which countries found it *particularly* more important than others?
- Which countries appeared unphased?
- What countries weren't allowed to talk about it (no Twitter access)?
- How do the 2016 Presidential candidates feel about the Thaw?"

Initially, the project had an audacious goal. We were going to determine how the world, the nation and each state felt about the US's new policy towards Cuba by extracting a sentiment value from each record in a dataset of 1 Million tweets from the date of the announcement and then visualizing this dataset by projecting the tweets onto a map color coded with demographic information (ex. most hispanic/least hispanic counties) and election data (Republican vs Democrat counties). Not only would this include Twitter users, but also politicians.

Our bold and ambitious goal started to look less likely when we noticed that 92% of the data lacked the coordinate-based geo-data (lat/lng or polygon) that we thought we were getting. Our once bulging dataset went from 1,020,000 to ~9,000. But that didn't dampen our enthusiasm much because our map of the US still looked pretty cool and we had 9,000 tweets to use for the sentiment analysis.

Unfortunately, a little more than a week later, it became apparent that our goal was virtually impossible given the time limitations. A leader in semantic analysis and natural language processing, Semantria awarded us a grant of several thousand credits(api calls) to use for our project, but after dozens of hours of tweaking Semantria's sentiment engine with custom dictionaries and other natural language processing optimizations, it was clear that it would take weeks if not months to fully optimize Semantria's algorithms such that the accuracy of the results would be high enough to allow us to make bold political declarations in our visualization. Highly sarcastic and often tangential political comments are rather difficult for many humans to properly understand, much less a computer.

At the eleventh hour, nervous about the project and unsure of our ability to deliver something "awesome", we brainstormed for alternate ideas.

During our brainstorming we tumbled upon a couple tutorials that explain how to geo-code location strings. We got to work and after the usual slow start, we were successful at geo-code almost 990,000 records. Again we had our full dataset that spanned the world.

Our solution was to double down on Big Data and put the user's focus on a global tweet map that visualizes the tweets at 20 times faster than realtime while specifying also if the tweet is original, a retweet, or a favorited tweet. This was a doable but very ambitious goal on both a technical and visual level and thus met our target for an "awesome" project.

# Data

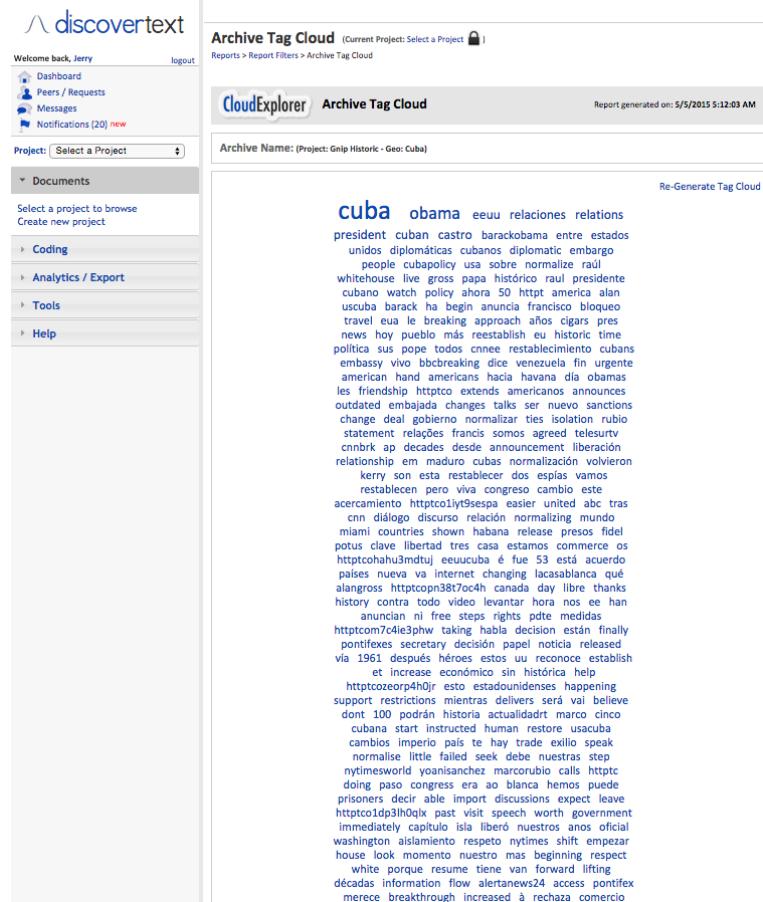
*Source, scraping method, cleanup, etc.*

We acquired the data through DiscoverText, an approved distributor of Twitter data.

Data consisted of 1,020,000 records each containing a tweet along with extensive metadata.

The screenshot shows the DiscoverText web interface. The left sidebar includes links for Dashboard, Peers / Requests, Messages, Notifications (20 new), Project (Grip Historic - Geo\_Cub...), Documents (with a tree view of Data Archives, Buckets, and Datasets), Coding, Analytics / Export, Tools, and Help. The main area is titled "Search and Browse Archive" with a sub-section "Has\_Geo\_Cuba-5 (Arch New tab)". It displays a list of 99,974 tweets from 100,000 total, showing various tweets from users like @rtarze, @eliaspino, @marcorubio, and @BarackObama. The interface includes filters, a search bar, and navigation controls.

*Data query in DiscoverText.com*



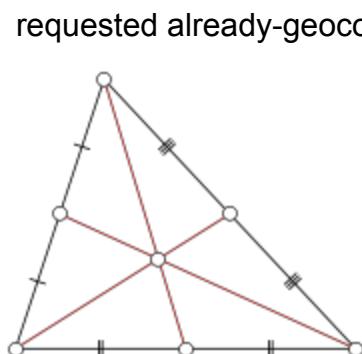
*Discovertext had some basic word cloud features that gave us our first exploration into the data, albeit a very broad one.*

Has_Geo_Cuba_9-export-20150412-113248.csv																										
	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD	AE	AF	AG	AH	AI	AJ	
1	[M] location_c	[M] location	[M] location	[M] location	[M] media_d	[M] media_t	[M] media_u	[M] posted_t	[M] real_name	[M] source	[M] statuses	[M] tweet_u	[M] user_bio	[M] user_loc	[M] user_me	[M] user_me	[M] user_tw	[M] username:								
2	r.com/chefAronna/statuses/545406969994289152								#ColombiaD Twitter for A	16131	http://www.Dedicated CI Colombia	NTN24	NTN24													
3	r.com/Bluegirl_3/statuses/54540697003762688								#ReneeBeau Twitter Web	2869	http://www.Politically ob WI	NowWithAle	NowWithAle												http://www.Bluegirl_3	
4	r.com/dbergman39/statuses/545406967217684480								#DanielBergn TweetCaster	1255	http://blogs.Commentante Nebraska	Wall Street J WSJ	Wall Street J WSJ													
5	r.com/famousred/statuses/54540698069115904								#GaryJ_Esme Twitter Web	482	J'ai une devi: La Baie	Nashua, NH	Top Conserv.TeaPartyCat													
6	r.com/GSeault/statuses/5454069970048806914								Gary J. Esme Twitter Web	482	Nashua, NH	Top Conserv.TeaPartyCat	http://www.GSeault													
7	r.com/gissellem/statuses/5454069897239056								#GisselleMori TwitterWeb	3353	http://www.Periodista de Cuba	Escambray, Fescambray	http://www.gissellem													
8	r.com/danicabre21/statuses/5454069897239056								#Dani Twitter for A	1925	http://www.Viajar y ser fi Lima - PerÃ	Noticias SIN SIN24Horas	Noticias SIN SIN24Horas													
9	r.com/angelcortez78/statutes/5454069897239056								#Dani Twitter for A	1925	http://www.Viajar y ser fi Lima - PerÃ	Noticias SIN SIN24Horas	Noticias SIN SIN24Horas													
10	r.com/Team_Galaxy/statutes/5454069898390174401								#CamilaFdez Twitter for A	3275	http://www.Twitter Se entrena en el gimnasio Pa Leonardo_P	http://www.camilecortez78														
11	r.com/67purple/statutes/545406968079955458								#cani_mapa Twitter Web	37052	http://twitte colorado girl Colorado girl Kenneth Iasa uselphant	http://www.67purple														
12	r.com/lulligrp/statutes/54540696820320360								#LuisMoreiraPlumÃs forÃ	26234	The views an Trujillo Alto, AndÃs Co andrescolon	http://www.lulligrp														
13	r.com/annmariaj/statutes/545406971985638416								#MiriamR Twitter for A	16759	Eduardo A Cerezo	ManoloReve	ManoloReve													
14	r.com/Parcial2/statutes/545406973445812225								#Tim Scanlon Twitter for W	30508	http://media Re-elect Mill Hyattsville, Maryland, USA	http://www.Parcial2														
15	r.com/tmcgev/statutes/54540697147524608								#TomMcGev Twitter Web	15232	Co-founder a New York	Tom McGevi tmcgev	http://www.tmcgev													
16	r.com/CV_People/statutes/54540697578624048								#Conservative Twitter for iF	26911	http://twitte Proudi folio USA	Ban Collectiv mregeology	http://www.CV_People													
17	r.com/aliaanamarria/statutes/545406971546206208								#LiliaAnna M IOS	24948	http://news Religious,53, Norway															
18	r.com/AttheistRaven/statutes/5454069738616502416								#AlaskanRave Twitter for A	21199	Aspiring supi Anchorage,	Top Conserv.TeaPartyCat	http://www.AtheistRaven													
19	r.com/Analog_Zero/statutes/545406974213779456								#Analog_Zero Twitter Web	13747	Barrangulla, Hassan Nassi HassHassar	http://www.Analog_Zero	http://www.cbarrons													
20	r.com/cbarrons/statutes/545406971759639825								#CÃSarBar Twitter for W	5947	http://www.Comienza tu DF															
21	r.com/frankalbaran/statutes/545406975815987200								#Franklin Twitter for A	1654	http://actual Chavista, Rev Venezuela	RT en EspaÃ ActualidadR	http://www.frankalbaran													
22	r.com/MTmarilyn2/statutes/545406972214423777								#MarilynOliver Twitter for W	144896	Retired smal Montana	Lonblonde	Lonblonde													
23	r.com/sospr_statutes/545406980068622336								#SoniaPress Twitterfeed	15045	http://www. Dios, Esposa, MÃxico															
24	r.com/eyranad97/statutes/54540697578624048								#Nges Twitter for A	1165	~ Assualmial seu,korea	MUJAHID SAFWANMU	http://www.eyranad97													
25	r.com/Delgado_106/statutes/54540697623117056								#Ramn Andri Twitter for A	1385	Docente de l Yaracuy Veni Mario Sila LaHojaIaen	http://www. Delgado_106														
26	r.com/proyecto_eps_bt/statutes/545406977556080472								#JorgeMore Twitter Web	4364	Proyecto inn Maracay	MABEL BORG 2405mabel	http://www.proyecto_eps_bt													
27	r.com/DanyaSuarez/statutes/545406978089287680								#DanaySuarez Twitter for IF	1825	Management La Habana, Cuba															
28	r.com/betomonos5/statutes/545406977271025664								#BetoMoren Twitterfeed	10646	http://www. Mi novia y tu DF															
29	r.com/digdless/statutes/545406976507662336								#DamiÃnIg Twitterfeed	10644	http://www. DESCURRIM Ecatepec, MÃxico															
30	r.com/sospr_statutes/545406978646755568								#SoniaPress Twitterfeed	15044	http://www. Dios, Esposa, MÃxico															
31	r.com/Riverocontreras/statutes/545406979251138560								#ElixClemente Twitter Web	15241	http://www. Socialista, rev Venezuela	Fidel Castro fidelcastro	http://www.Riverocontreras													
32	r.com/Btbandgraaf_RMT/statutes/545406980151692								#BrieHandgra TwitterCaster	1455	http://monde l reporte Rocky Mount CNNMoney CNNMoney	CNNMoney	http://www.Btbandgraaf_RMT													
33	r.com/Kijesianan30/statutes/54540698022324208								#Kijesianan30 Twitter for A	18057	http://www. Venezuela VENEZUELA El monitor 11 ElMonitor18	El monitor 11 ElMonitor18	http://www.Kijesianan30													
34	r.com/mirn9marcos/Ross/statutes/54540698113769472								#Mirn9marcos Twitter Web	14247	http://www. Prensa 7 das USA Katherine Mc Katherinenm	http://www.mirn9marcos														
35	r.com/1776BettyRoss/statutes/54540698043936384								#Mirn9marcos Twitter Web	11064	http:// Les susÃcÃs MÃxico	Independent USA	Bill Domato Bill111; me	http://www.1776BettyRoss												
36	r.com/1776BettyRoss/statutes/54540698043936384								#ProudAmerican Twitter Web	13535	Doing my be Del Ray, Alexandria, VA	http://www. jalynhenton														
37	r.com/aiyinherent/statutes/54540698061375744								#JohnHenton Twitter for A	11293	Yonai Sanchez yoaini Sanchez	Yoani Sanchez yoaini Sanchez	http://www.Lenguaiz_2018													
38	r.com/Longueira_2018/statutes/54540698061375746								#PabloLong Twitter for IF	1745	http://www. TWITTER Chile	Yoani Sanchez yoaini Sanchez	http://www.Lenguaiz_2018													
39	r.com/mfaroootstat7/statutes/545406984552726528								#MFarooot Twitter for B	4072	http://www. Business Karachi Pakis Reuters Top Reuters	http://www.mfaroootstat7														
40	r.com/catharine_ceil/statutes/54540698627791361								#Catharine_Ceil Twitter	27628	Morelia, MichoacÃn															
41	r.com/Pamadrigal(statutes/545406986737549312								#Pamadrigal Twitter	37082	Amo las flores Morelia, MichoacÃn															
42	r.com/digitalcarmona/statutes/545406991068903680								#Jose LuisCar Twitter for A	2920	#calmtechno Granada, Spi The Teacher mai_magia															
43	r.com/INGJOSEMANUEL/statutes/54540698633538944								#JOSE RODRIG Twitter for B	17833	Ingeniero inc VENEZUELA															
44	r.com/droletnomata/statutes/545406986695627656								#NomaDroleln Twitter	48656	Electroneir MÃxico, DF															

Of 1 Million records, only 8,000 had exact coordinate data (geo-data in polygon type). The remaining records included only the self-reported location strings found in a user's profile. These strings often had spelling errors and sometimes they were completely nonsensical ("Neverland"). For most of the project, we wrote these records off and accepted them as useless data. And then, with slightly less than a week to go, we stumbled on "geocoding".

Geocoding turned our dataset from 8,000 to 1,000,000+. Geographic information was used with the maximum resolution available from the Twitter data stream. While we requested already-geocoded data from Twitter, surprisingly few tweets came back with

legitimate location coordinates. When coordinates were available, they were typically of the "Polygon" style, describing not a point, but an area. Any Polygon location coordinates we collapsed to the geometric center



(<http://en.wikipedia.org/wiki/Centroid>) of the polygon using standard techniques. While Twitter often failed to provide precise location coordinates, in contrast it almost always provided each user's self-reported location, which can be thought of as each user's "home base." Examples include:

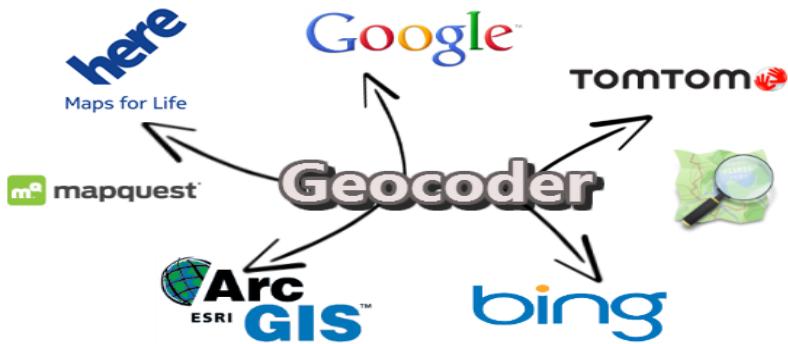
1. Cauquenes - Chile,
2. Boise, Idaho,
3. Johannesburg, SOUTH AFRICA,
4. Scotland.

While most are not precise to a street level, many are quite specific, giving state / regional location; some give an exact city, Others, however, are more whimsical:

1. planet tierra. o earth.
2. The Great State of Texas
3. North of where I came from
4. My underground lair.

Still others appear to be partial addresses, but are not sufficiently well-formed to be automatically converted into geolocations. For some of the missing data, a simple human edit was sufficient to reformat into a form that yielded a good geolocation; others simply had to be omitted as insufficiently geo-located / geo-locatable.

We then used the Python geocoder (<https://pypi.python.org/pypi/geocoder>) module to access an array of freely available web services provided by companies such as ArcGIS, Google, MapQuest, OpenCage, TomTom, Yahoo, and Yandex.



These services either transformed each textual location name / description into corresponding latitude and longitude coordinates, or reported failure in the attempt. In cases where no textual location was specified, or where the geocoder could not conclude the latitude/longitude from the text provided (occasionally with some manual assistance), we discarded the data point and did not display it on the map.

Because so many locations needed to be generated, it was important to use multiple geocoding services, so that we did not overload any one free service.

Once available to our web application in CSV and JSON formats, we used standard D3.js geographic projection functions ([API-Reference#d3geo-geography](#)) to map latitude and longitude into SVG display locations.

The size, color, and styling of display elements are dynamically chosen based on data attributes of each tweet. The radius of a tweet is log-proportional to the number of followers a tweeter has, giving an idea of the "reach" of the message. Whether a tweet is a retweet / retransmission of another message is also visually signaled (in yellow).

## **Tweet Timeline**

Tweets are displayed according to the time that they appear in the Twitter data stream. Tweets may occasionally stop displaying, or appear to pause. This is not an issue with the visualization, but rather a reflection of the fact that the Twitter data stream (at least as exported to us) lacks records for certain seconds.

For example, for one data file, the stream contains records for the following seconds:

0-44,  
59-539,  
553-562,  
568-599

But lacks them for seconds:

45-58,  
540-552,  
563-567

## **Data Cleaning and Preparation Pipeline**

The goal with any large data set is to have a large, useful, correct, and consistent set of data points. But big data is invariably "dirty." It contains errors, omissions, and inconsistencies. The process of preparing data for visualizations is similar to the "Extract, Transform, Load" ([ETL](#)) of the database community. In addition, data has to be prepared in such a way that it's easily consumed and used by the visualization process (which is usually running on a client device, often in the middle of an animation loop) where there is little to no opportunity for significant data cleanup.

While the sparkle and flash of graphical animations are often seen as the high point of visualization, just as important, if not more so, are the quality, quantity, relevance, and impact of the underlying data that is most important. The process of cleaning and structuring the data for visual display is the proverbial "rest of the iceberg" that lies beneath the waterline.

	A1	B1	C1	D1	E1	F1	G1	H1	I1	J1	K1	L1	M1	N1	O1	P1	Q1	R1
1	luzx "Title"	Text	Untitled	[M] country_cc	[M] favorites	[M] follower	[M] friends	[M] hashtag	[M] id	[M] is_retwe	[M] link	[M] location	[M] location	[M] location	[M] media_d	[M] media_t	[M] media	
2	RT @NTN24: [Video] #cuba @igabin cuman segu	2	510	820	tag=search.twitter.com	20	http://twitter.com/chefaromana/statuses/5450469994829152											
3	RT @NOMANOLITO: Cuba ame 3	183	418	tag=search.twitter.com	20	http://twitter.com/normanolito/statuses/545046997003762886												
4	RT @AVG: The USA and Cuba will remain relatives after 5 decades	292	312	tag=search.twitter.com	20	http://twitter.com/avg/statuses/54504699700448480												
5	RT @Lemicrodec: Rapprochement USA-Cuba	7	19	tag=search.twitter.com	20	http://twitter.com/lemicrodec/statuses/54504696809115904												
6	RT @TeaPartyCat: That awkward moment when Reg	5	22	tag=search.twitter.com	20	http://twitter.com/TeaPartyCat/statuses/54504696809115904												
7	Relaciones #Cuba Estados Unidos el deshielo por medio mu	463	352	Uba; Estad	tag=search.twitter.com	20	http://twitter.com/gisellemln/statuses/5450469688832920132											
8	RT @rededelacuba: Cuba#Cuba y Estados Unidos el restaurante el restableci	359	356	video	tag=search.twitter.com	20	http://twitter.com/rededelacuba/statuses/5450469688832920132											
9	RT @rededelacuba: RT @theheadlyheat: Other countries that 10 Pres	68	217	tag=search.twitter.com	20	http://twitter.com/cam_vallejo/statuses/545046968899170451 pic.twitter.cc photo												
10	RT @Leonardo: Dá a sí@rtico USA o Cuba	97	1325	tag=search.twitter.com	20	http://twitter.com/leonardo/statuses/545046968899170451 pic.twitter.cc photo												
11	RT @selephan: #Iwallowahwiblog: "Hurry up with their Cigars,	2092	2224	tag=search.twitter.com	20	http://twitter.com/67purple/statuses/545046997095586 pic.twitter.cc photo												
12	@DjLuisito: Hoy se cumple el 5 de diciembre y creemos a no hay? #ElPoderoso sysadmine a 40+	408	2688	tag=search.twitter.com	20	http://twitter.com/djluisito/statuses/545046997095586 pic.twitter.cc photo												
13	RT @Manuelito: RT @Manuelito: Cuba Comienza a tener relaciones con Cuba	1408	587	tag=search.twitter.com	20	http://twitter.com/manuelito/statuses/545046997095586 pic.twitter.cc photo												
14	Right-Wing Meets Right-Wing Media Lash Out After Havana Announces Deal With Cr	89	390	tag=search.twitter.com	20	http://twitter.com/annavannatta/statuses/5450469719562816												
15	@trmcgve First! Imgev First! boda es Cuba; second is Turkey; third is Egypt ...	3421	1008	tag=search.twitter.com	20	http://twitter.com/trmcgve/statuses/54504697174524608												
16	RT @mrcorona: #GeoLog: Raúl Castro pregonó la paz en su discurso	113	3147	2921	tag=search.twitter.com	20	http://twitter.com/mrcorona/statuses/54504697174524608 pic.twitter.cc photo											
17	What's New in the World of Twitter? In Today, and Why You Should Care	136	1350	tag=search.twitter.com	20	http://twitter.com/whatstnew/statuses/54504697174524608 pic.twitter.cc photo												
18	RT @TeaPartyCat: That awkward moment when Reg	296	495	tag=search.twitter.com	20	http://twitter.com/TeaPartyCat/statuses/54504697174524608 pic.twitter.cc photo												
19	RT @HassNassR: #HassNass: Cambien relaciones con Cuba mica	18	2487	2729	tag=search.twitter.com	20	http://twitter.com/HassNassR/statuses/54504697174524608 pic.twitter.cc photo											
20	EU-Ofrecen ayu a Peña para resolver diferente mar-timo cc	358	760	tag=search.twitter.com	20	http://twitter.com/charromarion/statuses/54504697174524608 pic.twitter.cc photo												
21	RT @ActualidadRT: ActualidadRT: #DíadelCastro: 'Debemos aprieta	157	385	EUba; Cuba	tag=search.twitter.com	20	http://twitter.com/actualidadrt/statuses/54504697174524608 pic.twitter.cc photo											
22	RT @Lionblonc: RT @Iwallowah: Those Criticizing 'President Obama'	45	3825	4106	tag=search.twitter.com	20	http://twitter.com/lionblonc/statuses/5450469722433777 pic.twitter.cc photo											
23	EU- Ofrecen ayu a Peña para resolver diferente mar-timo cc	415	729	tag=search.twitter.com	20	http://twitter.com/_osoya_/statuses/545046980068622336												
24	RT @SAFWANNAT: #SAFWANNATSAF No jajá bien, buenas relaciones	118	302	tag=search.twitter.com	20	http://twitter.com/safwanatasaif/statuses/545046980068622336 pic.twitter.cc photo												
25	RT @danielcastro: RT @danielcastro: Cuba Sí que tiene	39	39	tag=search.twitter.com	20	http://twitter.com/danielcastro/statuses/545046980068622336 pic.twitter.cc photo												
26	RT @2405mabre: RT @2405mabre: La feroz terrosta de Bush ahoga	2	850	1002	tag=search.twitter.com	20	http://twitter.com/proyecto_esp_b/statuses/5450469783610509472 pic.twitter.cc photo											
27	CUBA	12006	17	tag=search.twitter.com	20	http://twitter.com/DanyalSuarez/statuses/545046978092876860												
28	EU-Ofrecen ayu a Peña para resolver diferente mar-timo cc	493	831	tag=search.twitter.com	20	http://twitter.com/ardigless/statuses/545046978092876860 pic.twitter.cc photo												
29	EU-Ofrecen ayu a Peña para resolver diferente mar-timo cc	309	707	tag=search.twitter.com	20	http://twitter.com/ardigless/statuses/545046978092876860 pic.twitter.cc photo												
30	EU- Ofrecen ayu a Peña para resolver diferente mar-timo cc	415	729	tag=search.twitter.com	20	http://twitter.com/_osoya_/statuses/545046978647655686												
31	RT @Fidelcastro RT @fidelcastro: Kerr: Espera ser el primer Secret	6	1493	1484	tag=search.twitter.com	20	http://twitter.com/Riverocontreras/statuses/5450469752138560 pic.twitter.cc photo											
32	RT @CICPC: RT @CICPC: ¡Venga a la sede a la que te invita	114	77	123	tag=search.twitter.com	20	http://twitter.com/mauriciovalenzuela/statuses/5450469752138560 pic.twitter.cc photo											
33	RT @Monitor: RT @Monitor: 1878: Obama anuncia el fin del aislamiento a Cuba	558	100	tag=search.twitter.com	20	http://twitter.com/rtmonitor/statuses/545046978023211169 pic.twitter.cc photo												
34	RT @KatherineR: RT @KatherineR: Hey, let's go have fun in Cuba.	7	2633	2881	tag=search.twitter.com	20	http://twitter.com/illuvietoxestas/statuses/54504698117694972 pic.twitter.cc photo											
35	EU-Ofrecen ayu a Peña para resolver diferente mar-timo cc	361	885	tag=search.twitter.com	20	http://twitter.com/mm90marcos/statuses/545046981381435392												
36	RT @GOLDILL11: EU-Ofrecen ayu a Peña para resolver diferente mar-timo cc	516	777	Ketilly	tag=search.twitter.com	20	http://twitter.com/goldill11/statuses/545046981381435392 pic.twitter.cc photo											
37	Hoy comienza la Feria de las Naciones Unidas en Cuba. Sobre todo, que no se	1	401	401	tag=search.twitter.com	20	http://twitter.com/jpmoncayo/statuses/545046981381435392 pic.twitter.cc photo											
38	RT @yoanisante: RT @yoanisante: Así legál a d'A UN d'una column	49	4019	3611	GeneraciÁn	tag=search.twitter.com	20	http://twitter.com/longuera_2018/statuses/54504698607527566										
39	"@Reuters: US: Reuters: Cuba restores ties after 50 years http://to.vbc	7	51	tag=search.twitter.com	20	http://twitter.com/infraocafaz/statuses/54504698455276258												
40	Alista EU nueva Alista EU nuevas regulaciones para cargar embargo a Cuba	860	37	tag=search.twitter.com	20	http://twitter.com/catharine_cel/statuses/54504698627791361												
41	Alista EU nueva Alista EU nuevas regulaciones para cargar embargo a Cuba	823	41	tag=search.twitter.com	20	http://twitter.com/catharine_cel/statuses/54504698627791361 pic.twitter.cc photo												
42	RT @mal_magia: RT @mal_magia: Los cubanos podrán comprar A	232	284	tag=search.twitter.com	20	http://twitter.com/infodigitalcarmona/statuses/545046990168903680												
43	Es una valía entre gusanos y cubanos no la decidieron hoy, seguro q	990	1813	tag=search.twitter.com	20	http://twitter.com/NGOSEMANUEL/statutes/545046990168903680 pic.twitter.cc photo												
44	Alista EU nueva Alista EU nuevas regulaciones para cargar embargo a Cuba	581	41	tag=search.twitter.com	20	http://twitter.com/troleto_nonna/statuses/54504698659522656												

*Data files were sourced from Twitter in CSV format.*

Example cleanups include:

1. More accurately assess whether a tweet is a retweet or not. Twitter supposedly provides this information in a bespoke field, but even a cursory examination of the data shows it is often wrong. It neglects the text style retweet which starts "RT @userid". While Twitter may wish to consider only retweets using its (newer) native format to be proper retweets, its users clearly still prefer the old style.
  2. Locations. Twitter supposedly geo-locates tweets, but not very well or very often. When it goes to a location, it often does so as a very large geographical area (a polygon) which should be collapsed to a single point for plotting purposes. So we use publicly available geocoding services to translate self-reported user locations into geographical points.

We depend on both the accuracy of the user information (for both retweets and locations) and the accuracy of geocoding services (for locations). Realistically, there will be some errors in the resulting data, no matter how extensively we work to clean it up. Some users will mistype the conventional retweet marker (e.g. "RY @username"). Some will use non-standard, or at least non-English-standard, markers. Some will forget to mention they are copying others' content, or will use alternate quotation means (e.g. good old "quotes" and/or --attribution). When it comes to locations, some users don't provide accurate information, or use the field for metaphorical descriptions. The geocoders may misunderstand intent. *Et cetera.*

A benefit of working with large data sets is the [Law of Large Numbers](#). Yes there may be some errors, but they will generally be overwhelmed by the correct data that is displayed. Humans are pretty good at discarding outliers. The second virtue is visualization, which provides a high-bandwidth mechanism for humans to interact with data. If things are out of kilter, they have a high propensity to notice when there are corresponding visual effects and outcomes--much more so than if the data variances were hidden in otherwise dense textual formats or statistical aggregations.

Human oversight is reasonably important in managing such data pipelines, since you want to incrementally improve the data. It often helps to have someone watching early failures to realize that "You know, a lot of these geocoding failures are on locations that end with a period--and that period does seem out of place here. What if, on locations that fail on the first attempt, we remove the final period and try again?" Or "A lot of people sure do want to make their country #USA a hashtag."

Maybe geocoders aren't savvy to that. If we see things that look like a hashtag, let's remove that and try again." Such rule-based cleanups dramatically improve data coding effectiveness.

## Infrastructure

We used cloud servers to run the geocoding process, so that we could have multiple systems working on the problem at a time. We used 4 external servers at most times, bursting to 8 late in the process as our automation scripts became more mature.

Subdividing the data for the multiple servers was a bit of a chore. We wrote some simple `bash` (Unix shell language) scripts to help automate it, but more work there would be good for dealing with large data sets.

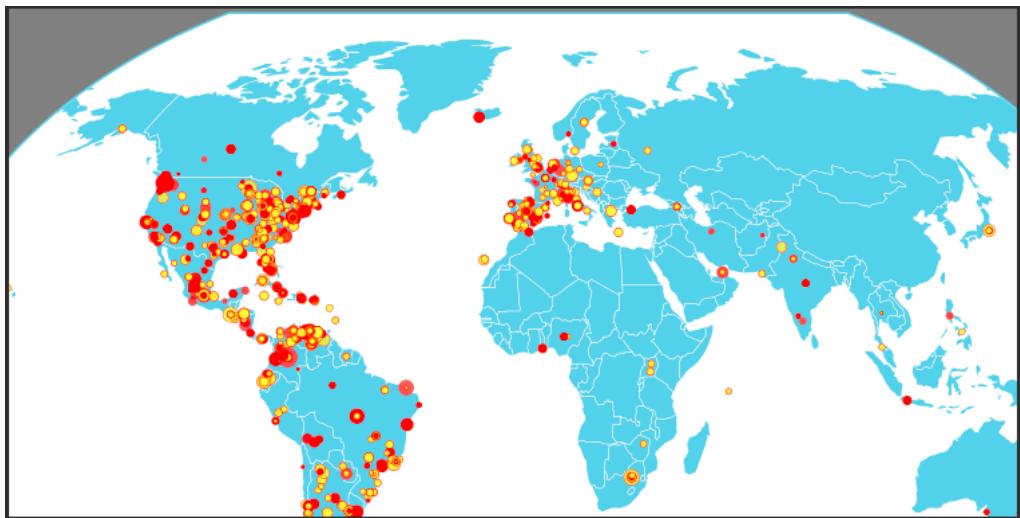
Spreading processing over multiple geocoding services was a net win, allowing us to process a very large number of requests and geocode almost a million tweets (where the original data only had a few thousand geocodes present). But dealing with multiple services introduces some variance. Google, MapQuest, and Google may not agree on the exact location of a place, for instance. They generally are very close--but it's not exact. Also, some geocoders can code some locations that others have trouble with. Geocoding automation was a huge win, but introduced its own complexities and a bit of variance in the resulting data.

## Animation Engine

The map-based animation of tweet occurrence uses the [D3.js](#) framework to plot [SVG](#) shapes against a geographic background. D3.js handles most of the heavy lifting of mathematically converting from latitude and longitude onto various map projections and thence onto SVG display coordinates.



We use two map projections, a [conic conformal projection](#) for the US map, and a [Kavrayskiy 7 pseudo-cylindrical](#) for the world map. Choosing a map projection is a balance between optimizing multiple competing geometric properties and achieving pleasing visual aesthetics.





The primary animation routine is quite short, basically pulling in a second-by-second array of animatable events via [JSON](#) and displaying them according to various properties. Larger tweets reflect larger follower counts for the tweeter, thus a larger addressable audience. Retweeted content ("someone else said...") is displayed in a lighter color (yellow) to reflect the lesser originally. Purple borders are applied for tweets that are favorited, indicating enthusiasm of reception.

Keeping the tweet animation "fed" is a significant responsibility, since it plays at upwards of 20x real-time display rates. Thus, if there are 15 or 20 geocoded and animatable tweets in a given second--not an unreasonable estimate--there will be 300 to 400 new animation objects added per second. Animations last up to 2 seconds, considering their emergence and then incremental dissipation, so there can be easily be 600 to 800 animations in progress at any given instant. Feeding this requires an optimized JSON format, which is prepared by our backend data cleanup.

But a vast number of optimizations were required before we could start to visualize Big Data.

We expected clean, uniform, and categorized data but unfortunately twitter data is actually very messy. We spent equal or more time in data wrangling / semantic analysis than in visualization.

The tools for semantic analysis are many, but we went with [Semantria](#) because they are strong supporters of visualization education and data research.

Though Semantria is the industry leader in text analytics, our dataset proved too unruly to handle in the limited amount of time afforded to us to complete the project. That time was further reduced because we had to acquire and install windows 8 on a virtual machine in order to use Semantria's tools in Excel. A virtual Windows 8 environment cost us a lot of ram and our programs ran much slower and less predictable. In fact, loading the csv data files would often cause excel to crash. Furthermore, before we could run a viable semantic analysis of the data we had to do even more cleaning to remove special characters that gave Semantria trouble in addition to writing an N-gram text categorization algorithm to identify and sort the tweets by language in order to improve Semantria's accuracy when running a single configuration of the engine over a multi-language dataset.

All of this slowed our progress, but the fact that we only had a limited number of API calls meant, that we had to put serious thought into every batch and that realization reduced our agility.

## **Exploratory Data Analysis:**

What visualizations did you use to initially look at your data? What insights did you gain? How did these insights inform your design?

- ❖ For most of the project, we were unable to do proper data visualization in our exploration because the data set was orders of magnitude larger than anything we were prepared for. We also lacked consistent, reliable, and easily usable geoData. DiscoverText had basic exploration functionality that we used primarily in the first 7-10 of the project.
- ❖ Our main visualization for the first two weeks or so was a slice of tweets mapped against the US shaded to Obama Romney election results.
- ❖ We learned that the semantic analysis of political tweets is very, very hard. You must develop custom dictionaries and weights for a variety of different objects such as entities, documents, phrases in addition to ensuring robust language detection (n-gram categorization).
- ❖ Our realization that a proper semantic analysis would not be feasible led to the pivot to try and visualize all the of the tweets in an accelerated time frame.

**TopMeta Discovery**

Top values for: country\_code:

Meta Value	Total	Filter
United States	746	
Venezuela	199	
Brasil	195	
España	128	
Chile	114	
México	93	
Colombia	91	
Argentina	85	
United Kingdom	51	
Canada	45	

Showing 1 to 10 of 57 total

### DiscoverText's exploration by country code

ID	Source Text	Summary	Detected Language	Detected Language String	Document Sentiment	Phrase Intensity	Phrase Negate	Phrase	Phrase Sentiment	Phrase Score	Entity	Entity Type	Entity Sentiment	Entity Sentiment Score
1	4712-4795- suffered enough! Let's move int	Cuba. The civilians have and help oppress some dissidents!!	English	English	0.052 neutral	EndThe embargo	0.4 positive	Cuba	Place	0.92 positive	Alex	Person	0.92 positive	7
1157	4537-9246- Cuba and Kim Jong-un are in an uncomfortable position. It'll be interesting to	Cuba and Kim Jong-un are in an uncomfortable position. How perfect!	English	English	0.493 negative	oppress	-0.392 negative	n't Obama	Place	-0.19 negative	7			
1158	4539-8849- GOP in an uncomfortable position. It'll be interesting to	Kim Jong-un and Castro brothers. How perfect!	English	English	0.493 negative	progress	-0.392 negative	Castro	Place	-0.19 negative	7			
1160	4597-8322- Colombia	day for the supreme	English	English	0.493 negative	interesting	0.49 positive	Cuba	Place	-0.93462 neutral	7			
1161	4597-8322- Colombia	day for the supreme	English	English	0.08012 neutral	good	0.5 positive	Cuba	Place	0.08012 neutral	7			
1162	4231-9364- the people of Cuba will have better lives because of this.	Argent talk about Cuba	English	English	0.06732 neutral	best	0.69 positive	NormalizacionOTG	Place	0.69 positive	7			
1163	4242-8264- Happy Homeland to Alan and Judy Gross! Cuba...	Obama talk about Cuba	English	English	0.2 neutral	Hopefully	0.28196 positive	Cuba	Place	0.90240 positive	7			
1164	4242-8264- Happy Homeland to Alan and Judy Gross! Cuba...	Happy Homeland to Alan and Judy Gross! Cuba...	English	English	0.2 neutral	Happy	0.2 neutral	Alan	Person	0.5 neutral	7			
1165	4460-4115- cuba...this is a massive photo op and thumb in the eye	Happy Homeland to Alan and Judy Gross! Cuba...	English	English	0.2 neutral	still	-0.39092 negative	Judge	Person	-0.39092 negative	7			
1166	4460-4115- cuba...this is a massive photo op and thumb in the eye	Happy Homeland to Alan and Judy Gross! Cuba...	English	English	0.2 neutral	freedom	-0.82956 negative	photo	Place	-0.1184 neutral	7			
1167	4460-4115- normalization with Cuba	normalization with Cuba	English	English	0.2 neutral	head	-0.21111 neutral	Castro	Place	-0.21111 neutral	7			
1168	4460-4115- normalization with Cuba	normalization with Cuba	English	English	0.2 neutral	Huge	0.08 neutral	Never lie	Ed	Company	0.5 neutral	7		
1169	4460-4115- normalization with Cuba	normalization with Cuba	English	English	0.2 neutral	only	0.0565354 neutral	Cuba	Place	0.1540846 neutral	7			
1170	4460-4115- Many places there includes publishing health...	European ones	English	English	0.2 neutral	European rights	0.0565354 neutral	writing	Place	0.1233333 neutral	7			
1171	4460-4115- Many places there includes publishing health...	policy on Cuba, long	English	English	0.2 neutral	So	0.75 positive	Many places	Place	0.058 neutral	7			
1172	4242-8264- Not quite such good news for Vladimir Putin...	Cuba likes are a win for	English	English	0.2 neutral	win	0.3298421 positive	US	Place	-0.0234242 neutral	7			
1173	4242-8264- Hispanic vote: Cubans in Miami have been able to	Cuba likes are a win for	English	English	0.2 neutral	classic	0.49 positive	Cuba	Place	-0.19 neutral	7			
1174	4242-8264- CartoonistsAgenciesCrime is 1995, my strongest	window dressing	English	English	0.2 neutral	pandering	-0.4 negative	votes	Place	-0.1184 neutral	7			
1175	4242-8264- CartoonistsAgenciesCrime is 1995, my strongest	CartoonistsAgenciesCrime is 1995, my strongest	English	English	0.2 neutral	principled	0.596 neutral	Cuba	Place	0.5 neutral	7			
1176	4242-8264- policy. In real life, it was Ben Rhodes	of the	English	English	0.2 neutral	Cuba	-0.2404520 negative	Provider	Job Title	-0.037959 neutral	7			
1177	4242-8264- policy. In real life, it was Ben Rhodes	who orchestrated the	English	English	0.2 neutral	real life	0.212 neutral	Leo	Person	0.058 neutral	7			
1178	4242-8264- President of Cuba for	President of Cuba	English	English	0.2 neutral	in	0.056 neutral	Ben Rhodes	Person	0.49 neutral	7			
1179	4242-8264- Runs Congress to Entice Cuba. 3. Shortage solved!	President of Cuba for	English	English	0.2 neutral	thankful	0.5880001 positive	Senator	Job Title	0.49 neutral	7			
1180	4242-8264- President of Cuba for	President of Cuba for	English	English	0.2 neutral	Embrace	1.1 positive	Cuba	Place	1.1 positive	7			
1181	4242-8264- Zimbabwe, and Egypt Regimes that use torture are bad!	Zimbabwe, and Egypt Regimes that use torture are bad!	English	English	0.2 neutral	bad	-0.54 negative	as isolated	Place	-0.2442222 neutral	7			
1182	4242-8272- Zimbabwe, and Egypt Regimes that use torture are bad!	isolated as China	English	English	0.2 neutral	bad	-0.56 negative	Myanmar	Place	-0.39455 neutral	7			
1183	4242-8272- Zimbabwe, and Egypt Regimes that use torture are bad!	isolated as China	English	English	0.2 neutral	torture	-0.56 negative	Zimbabwe	Place	-0.39455 neutral	7			
1184	4242-8272- relationships with Cuba after all the human rights	isolated as China	English	English	0.2 neutral	bad	-0.2030001 negative	Iraq	Place	-0.39455 neutral	7			
1185	4242-8272- relationships with Cuba after all the human rights	would try to normalize	English	English	0.2 neutral	violations	-0.2 negative	n't believe	U.S.	Place	-0.2 neutral	7		
1186	4242-8272- relationships with Cuba after all the human rights	would try to normalize	English	English	0.2 neutral	violations	-0.2 negative	Cuba	Place	-0.2 neutral	7			
1187	4242-8272- relationships with Cuba after all the human rights	would try to normalize	English	English	0.2 neutral	imposed	0.158 neutral	Castro	Place	0.45 neutral	7			
1188	4242-8272- relationships with Cuba after all the human rights	would try to normalize	English	English	0.2 neutral	tyrants	-0.6 negative	Marco Rubio	Person	0.45 neutral	7			
1189	4242-8272- relationships with Cuba after all the human rights	would try to normalize	English	English	0.2 neutral	no	0.42 neutral	Obama	Person	0.10985 neutral	7			
1190	4242-8272- relationships with Cuba after all the human rights	would try to normalize	English	English	0.2 neutral	Jewish pop	0.42 neutral	John Gross	Person	0.10985 neutral	7			
1191	4242-8272- relationships with Cuba after all the human rights	would try to normalize	English	English	0.2 neutral	terrorists	-0.27244 negative	Cuba	Place	0.6812 negative	7			
1192	4242-8272- relationships with Cuba after all the human rights	would try to normalize	English	English	0.2 neutral	restoration	0.492857 positive	Iran	Place	0.6812 negative	7			
1193	4242-8272- relationships with Cuba after all the human rights	would try to normalize	English	English	0.2 neutral	diplomatic ties	0.139804 neutral	China	Place	0.2075400 neutral	7			
1194	4242-8272- relationships with Cuba after all the human rights	would try to normalize	English	English	0.2 neutral	president	0.2375400 neutral	Real Castro	Person	0.2375400 neutral	7			
1195	4242-8272- relationships with Cuba after all the human rights	would try to normalize	English	English	0.2 neutral	president	0.2375400 neutral	U.S.	Place	0.2375400 neutral	7			
1196	4242-8272- relationships with Cuba after all the human rights	would try to normalize	English	English	0.2 neutral	worst	-0.196 negative	president	Job Title	-0.086937 neutral	7			

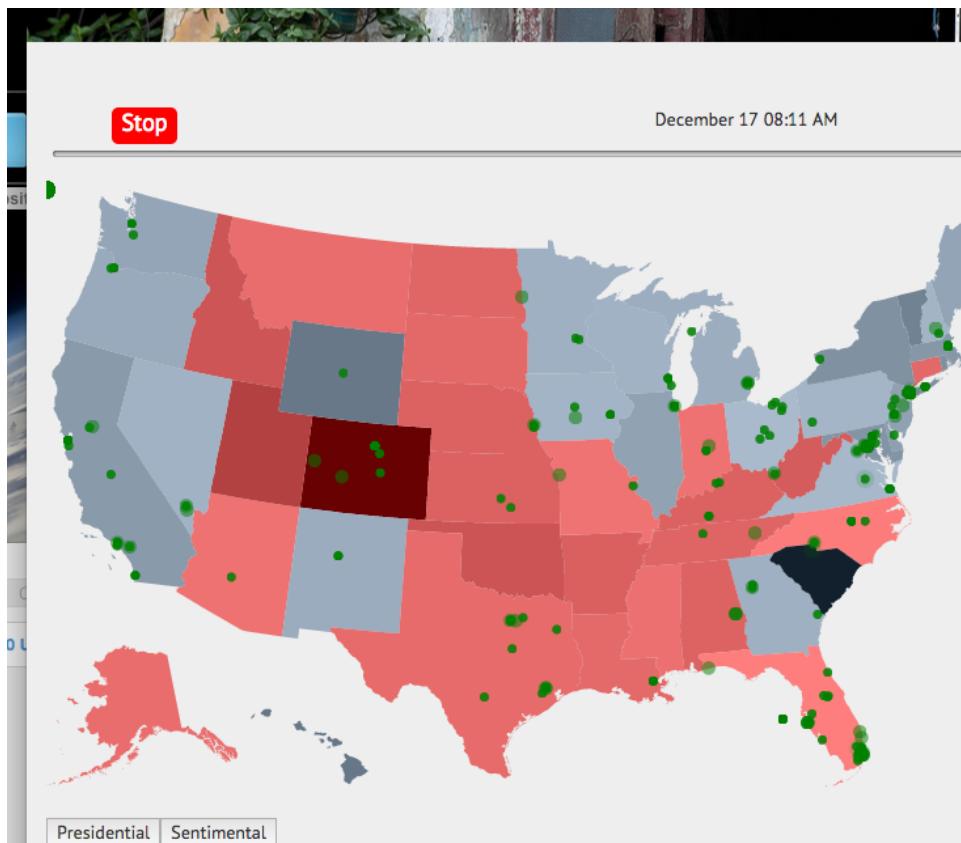
Semantria's tools also allowed us to see the common phrases, objets, languages, and emotions in the data.

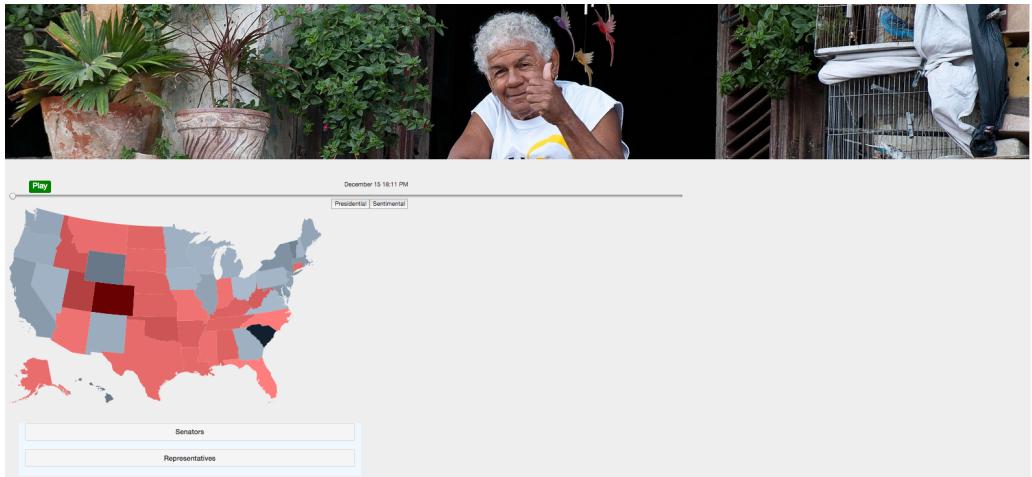


## **Design Evolution:**

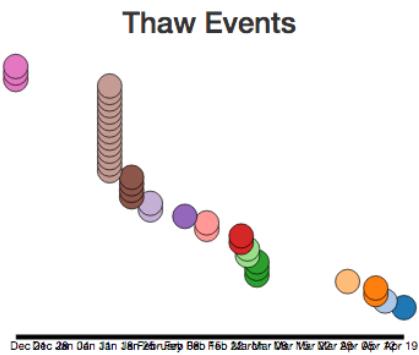
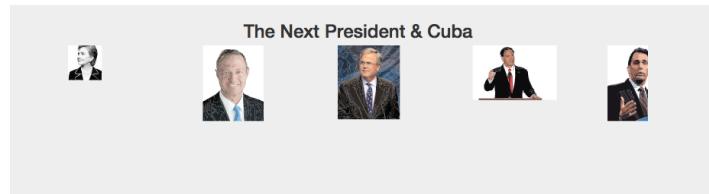
- ❖ We struggled choosing colors for tweets and maps. Ultimately we decided to keep the maps a single color and the tweets could be one of 3 color combinations. This decision was based on the fact that with tens of thousands of tweets populating the screen, multiple colors on multiple backgrounds would be too much.
- ❖ Deciding between greater precision and greater aesthetics. Because a small subset of the tweets used a rectangular area as its location, we decided on resolving this to a single lat/lng point because it improves aesthetics. The visual benefit is more important than a slight deviation in the integrity of the data.
- ❖ Deciding whether to aggregate and how to aggregate. We did not aggregate any tweets although we did do some aggregation of tweets over time. That is, if a group of tweets occurred extremely close to each other, we would display them as if they occurred at the same time. This improved performance considerably due to caching.
- ❖ Semantic analysis posed difficult aggregation questions. “If your visualization is correct on average but internally it is very volatile and wrong, is it a good visualization?” This consideration, and our belief that the process is as important as the results, also influenced our decision to pivot.
- ❖ Choosing a “One page” website design over a traditional multi-page design in terms was a decision that improved storytelling by forcing a linear path for the user’s eyes as they travel down the site.

The image below was our main visualization for most of the project, a map of the US with using a small subset of the full dataset (8,000 vs 1,000,000+). Colors were meant to represent either states Obama won or Romney won, but the actual color is just a basic prototype choice.

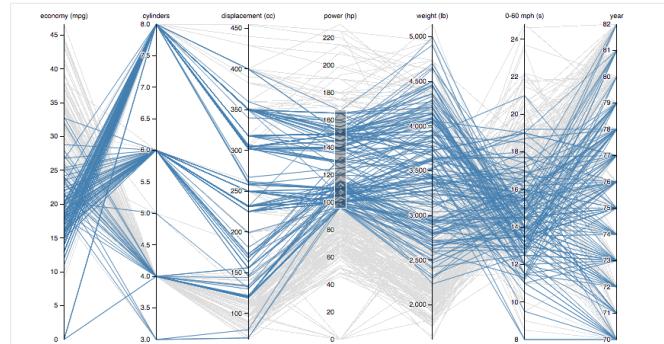




The other visualizations, while a part of the project, were more ornamental and ancillary to our main goals. Seen below in rudimentary form, the President and NYT API Brush visualizations still made it into our final project.

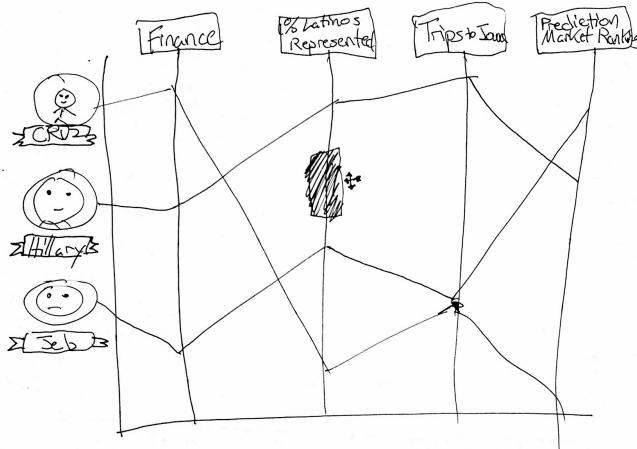


## Parallel Coordinates



This is a version of Mike Bostock's [parallel coordinates example](#), modified to include reorderable axes.

[Open in a new window.](#)



## PARALLEL COORDINATES

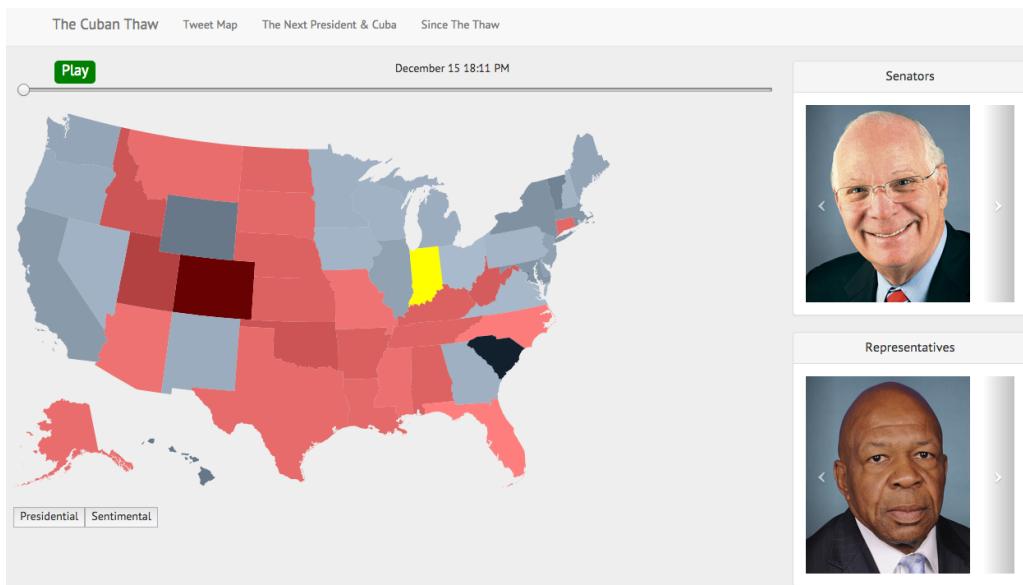
During our milestone one meeting, we discussed with our TF about turning the visualization of presidential candidates into a Parallel Coordinates visual. While technically interesting and visually complex, we feel that this interface is too advanced for our expected users and their use cases. It is neither the most intuitive solution nor the most promising of insights given that we know apriori that party affiliation has by far the strongest predictive ability given how most candidates agree very closely with party

line. Of all the potential presidential candidates, only one (Rand Paul) goes against his party's official opinion (He supports it).

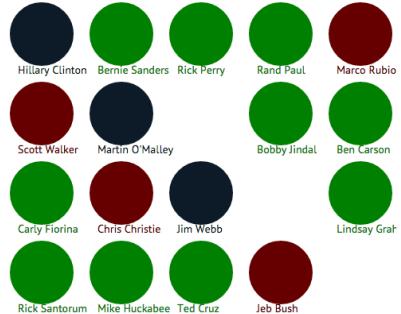
Directly below are those same visualizations albeit in a more intermediate state.

**Note:** The Congress visualization was dropped after extensive research made it clear that there was not enough variance within the parties to be able to show meaningful data.

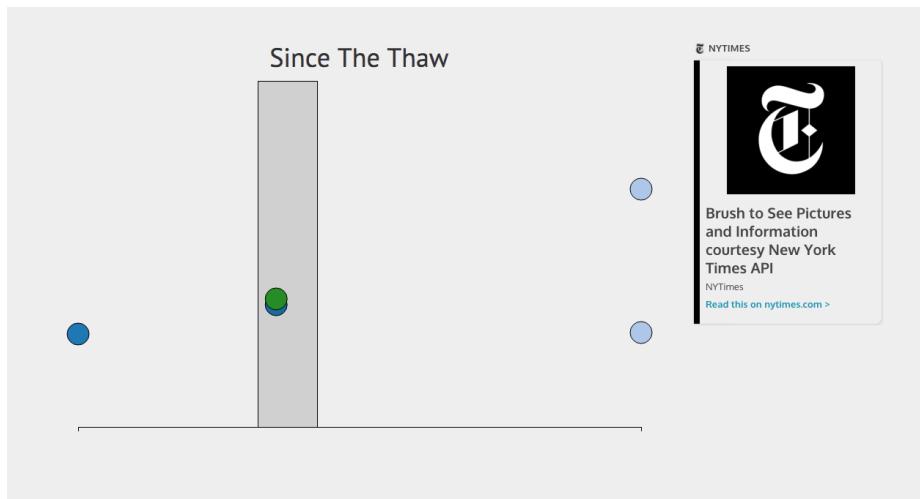
---



## The Next President & Cuba



[For | Against]

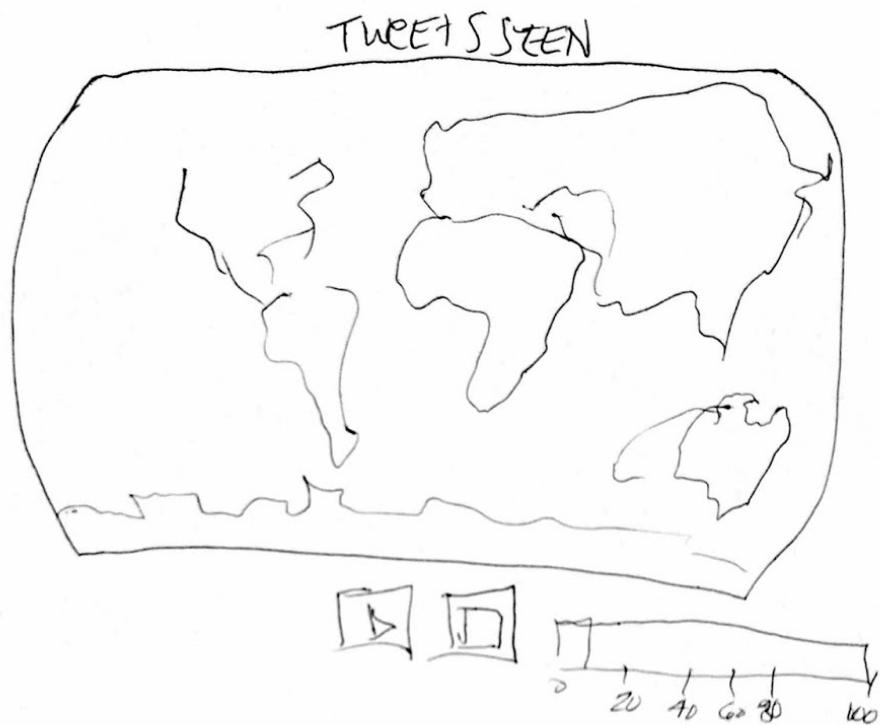


*This brush queries the NYTimes for articles related to Cuba between the brush's extent.*

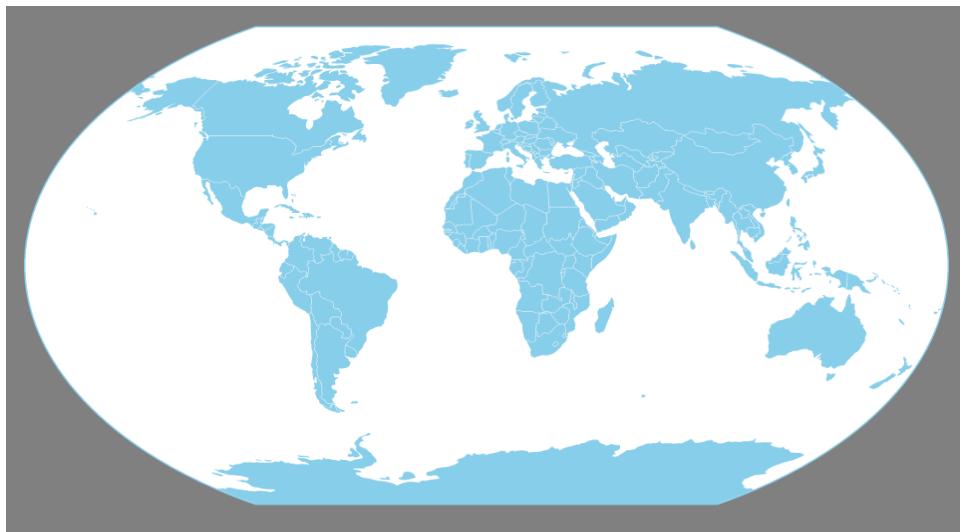
## The Project Pivot.

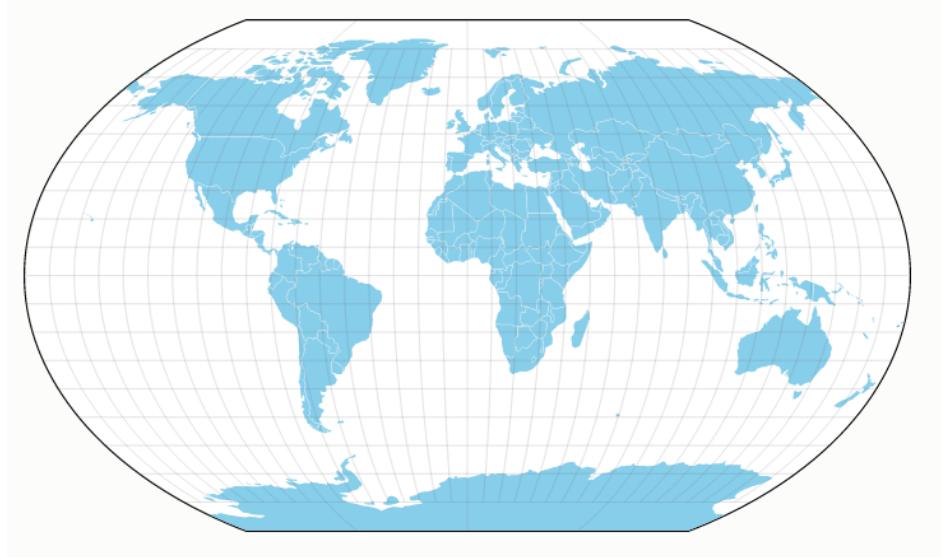
*Below this line are images we produced after the project changed course from the initial proposal.*

---

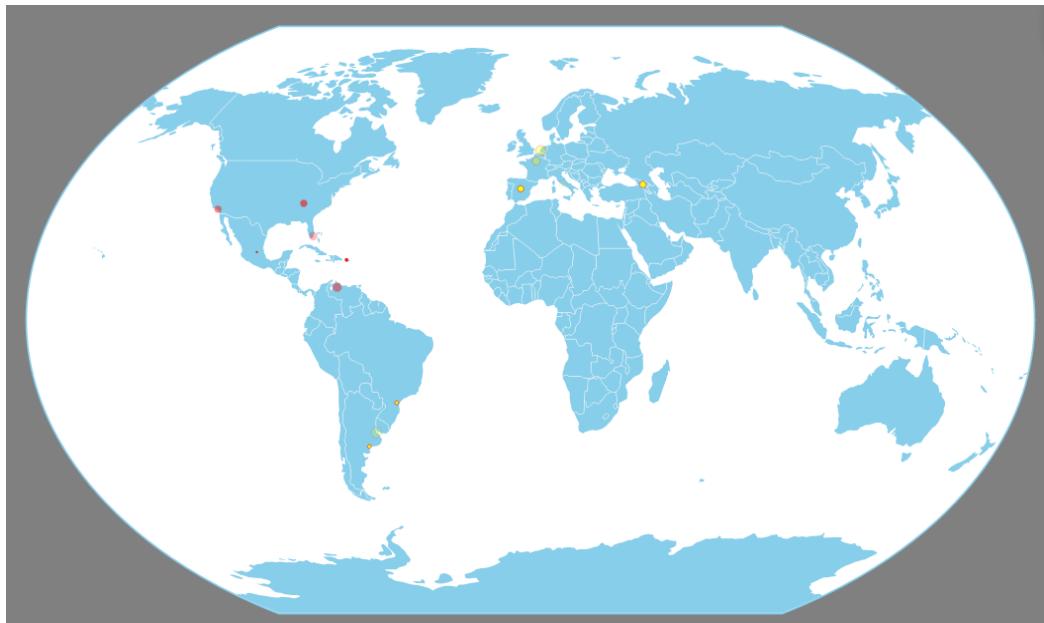


*An initial, basic sketch of our map visualization.*

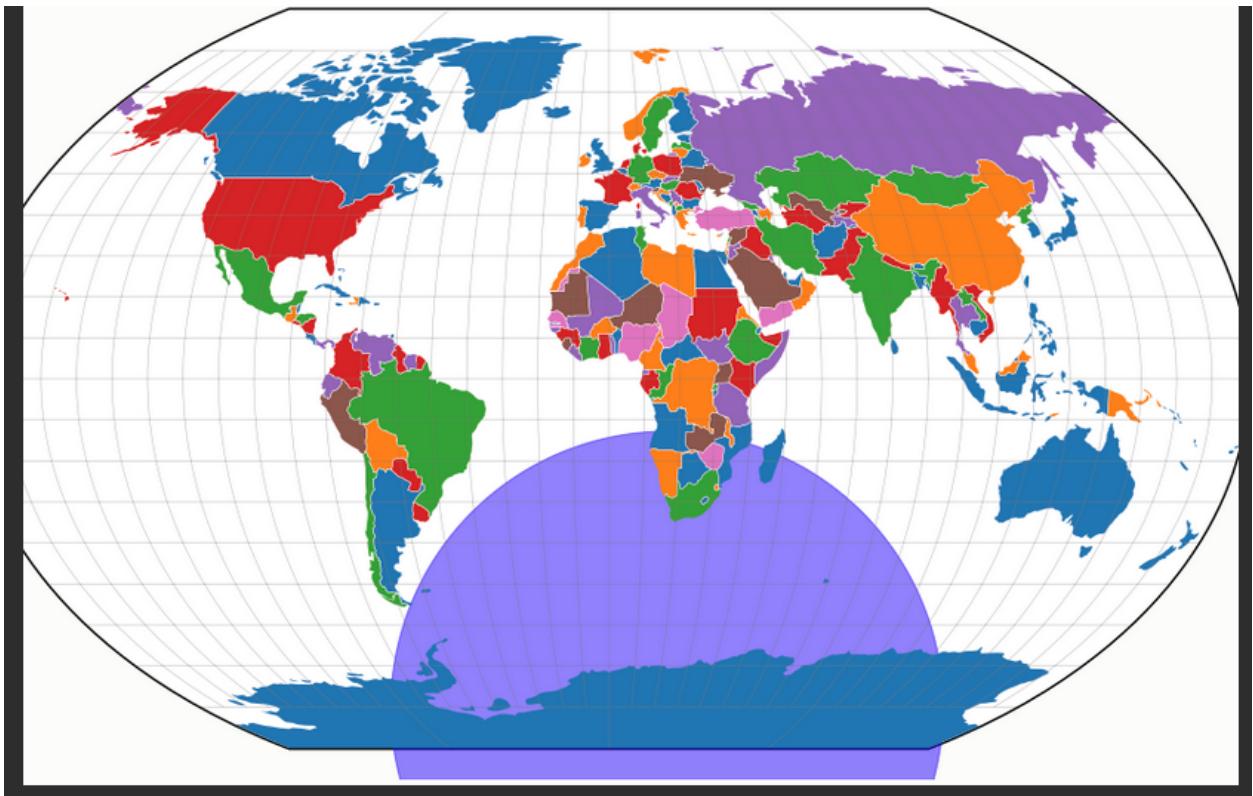




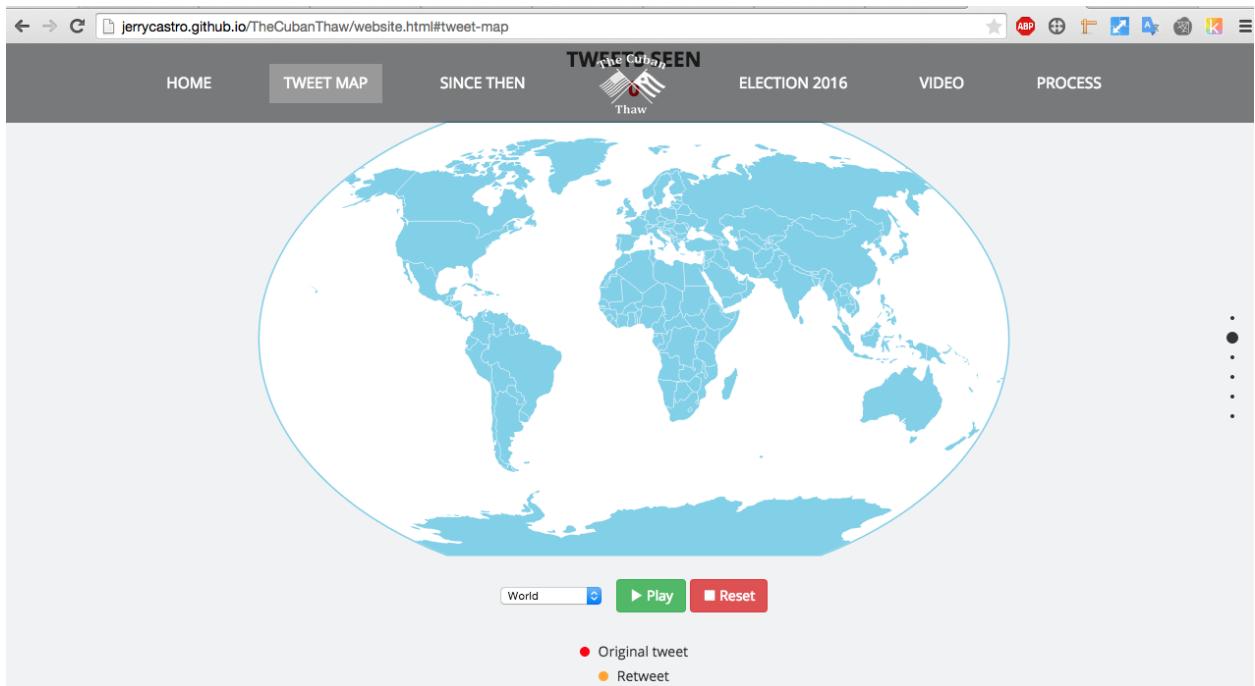
*Choosing what kind of projection and what colors to use was a non-trivial decision, but ultimately we based it on aesthetics.*



*Our first test visualizing a couple points onto a global projection.*



*Sometimes things happen in testing that you can't explain....*

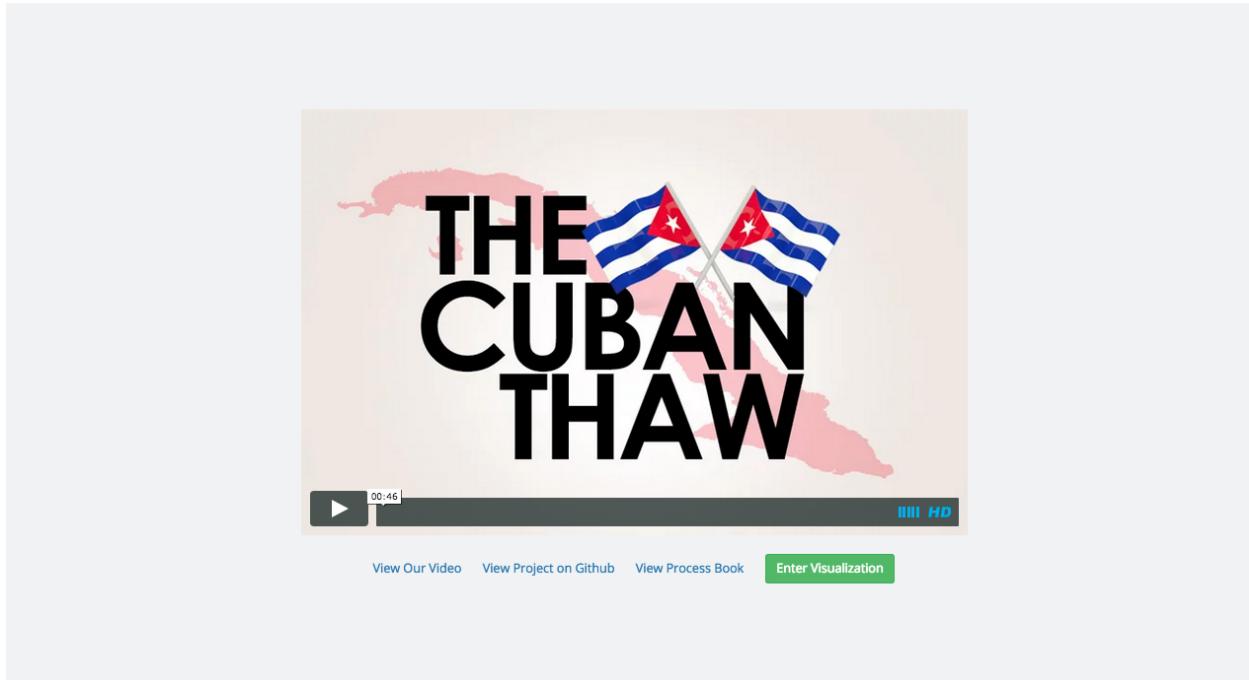


*A near final representation.*

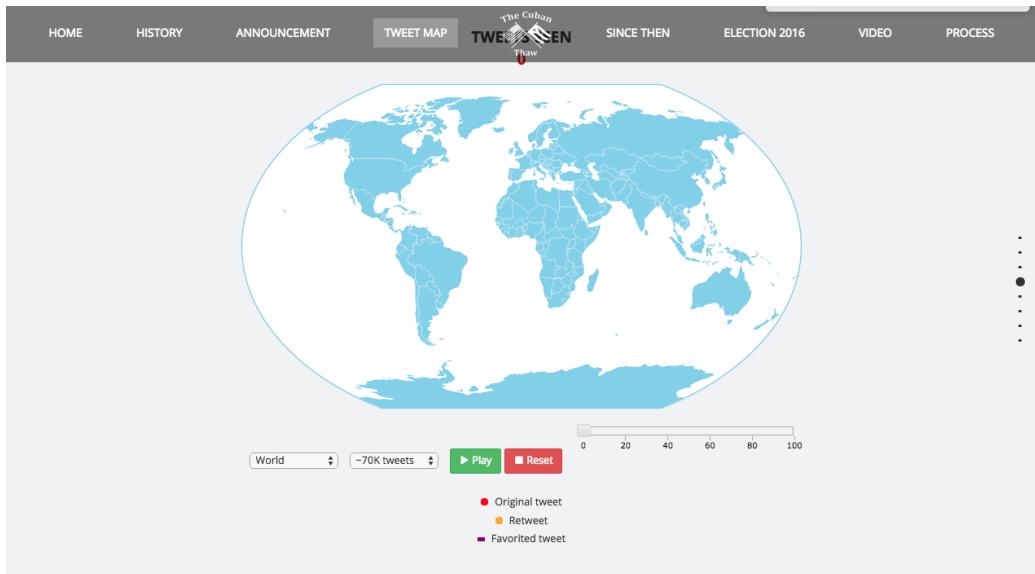
## Implementation

Describe the intent and functionality of the interactive visualizations you implemented.

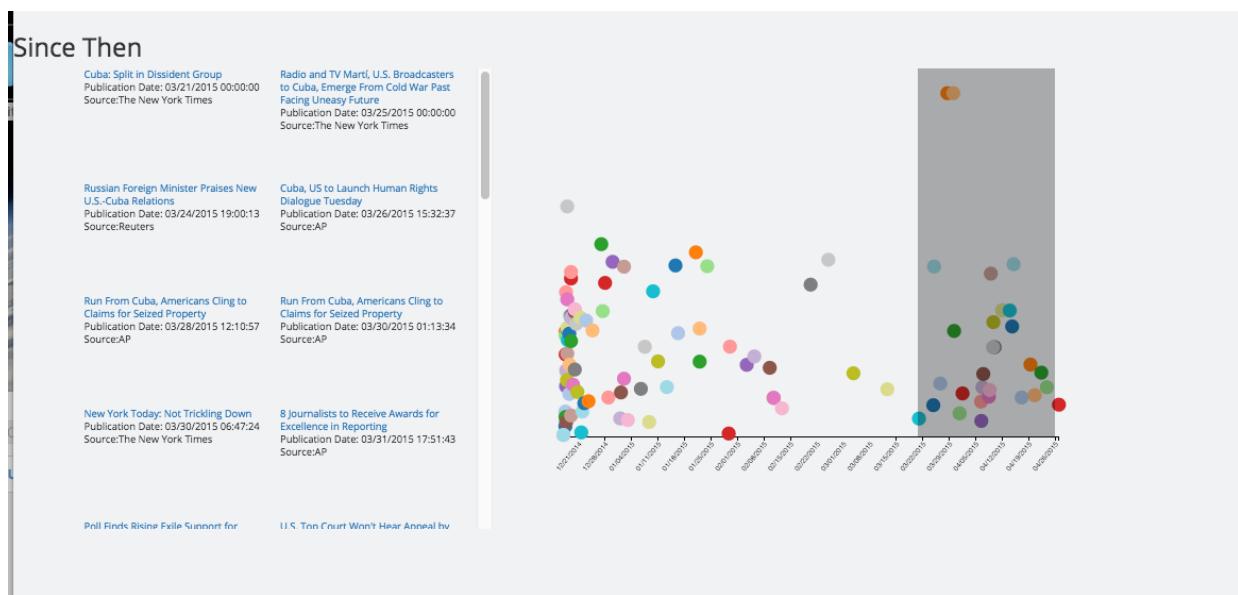
Provide clear and well-referenced image



This intro video gives all users some historical context while creating excitement for the visualization. Links are provided for those users that know exactly what they want to see.



*This is the tweet map of our dataset playing at 20x faster than real time. Users may select whether they want to see a world or a US-only map.*



*Brush against this graph of NY Times API results based on a query to find all articles related to the Thaw. Articles appear on the left with links and source data.*

HOME    TWEET MAP    SINCE THEN        ELECTION 2016    VIDEO    PROCESS



Chris Christie  
Republican  
Support: maybe

*Hover over a Presidential candidate to see whether or not she approves of the new Cuba Policy.*

## Evaluation

The Thaw crossed into the mainstream conversation with many ordinary people commenting on it and the historical significance of the US embargo of Cuba was a very big deal to people in Latin America and Europe. We also noticed that even though Twitter skews young, Florida still erupted with activity indicating a young Cuban population is likely to be politically engaged which could prove dangerous to some politicians.

We had no idea that Venezuela's Twitter had such an extensive presence until we finally saw it in the visualization. Venezuela has been Cuba's closest ally over last 10 years. That relationship ended first with death of Hugo Chavez and now the collapse of oil which Venezuela's economy depends on as it is one of the largest exporters of petroleum in the world. With the Cuban Thaw occurring on top of the economic havoc and political turmoil in that country, it is obvious in hindsight that the people of Venezuela would be especially vocal on Twitter, but of course it took the visualization for us to see this.

Ultimately, we chose this dataset because we felt strongly that it is truly a significant piece of history. Not only does it capture a historical detente in Americas, but it does so using the natural expressiveness and stream of consciousness style that Twitter is famous for. This dataset will one day allow future historians to read the mind of humanity which we think is the future of historical record keeping.

## Improvements

- ❖ Take 2-3 months and dive extremely deeply into semantic analysis (not recommended, there are better, less technical ways albeit with less originality).
- ❖ Given that tweets can be either retweets to your followers or just an original comment or thought, we can build a graph of tweets to show the flow of information. Flow of tweets between cities. If Miami's tweets are indeed against the new policy, than interesting links would emerge between Miami and more rural anti-Obama areas.
- ❖ We could have tweets of a certain hashtag increase the proportion of that color in a countries color, thus a country takes on the color of it's most popular hashtag.
- ❖ The slider can be upgraded to be made much more responsive but there is a limit to what we can do because with the full data playing, we are certainly approaching the outer edges of animation in the browser.