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The Cuban Thaw

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Overview and Motivation

Provide an overview of the project goals and the motivation for it.

Our projects primary goal is to

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 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

Anything that inspired you, such as a paper, a web site, visualizations we discussed in class, etc.

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.

Questions

What questions are you trying to answer? How did these questions evolve over the course of the project? What new questions did you consider in the course of your analysis?

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?
- What countries didn't appear to find it interesting 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 way of measuring the sentiment of a tweet. Thankfully, those tens of hours engaged in semantic analysis of the tweets

meant we both had logged countless hours staring at this data. All of it payed off when we finally realized that for a highly politicized event like the Cuban Thaw, the hashtags themselves are actual flags of sentiment.

During our brainstorming we also stumbled upon a couple tutorials that explain how to geo-code location strings. We got to work and after the usual repasted failers, we were successful at geo-coding 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. We designed it so that users would make their own sentiment judgements based on the contextual information in the visualization alongside a list of top hashtags. An embedded twitter feed also enriched the experience by allowing the user to consider the text of the tweet as well.

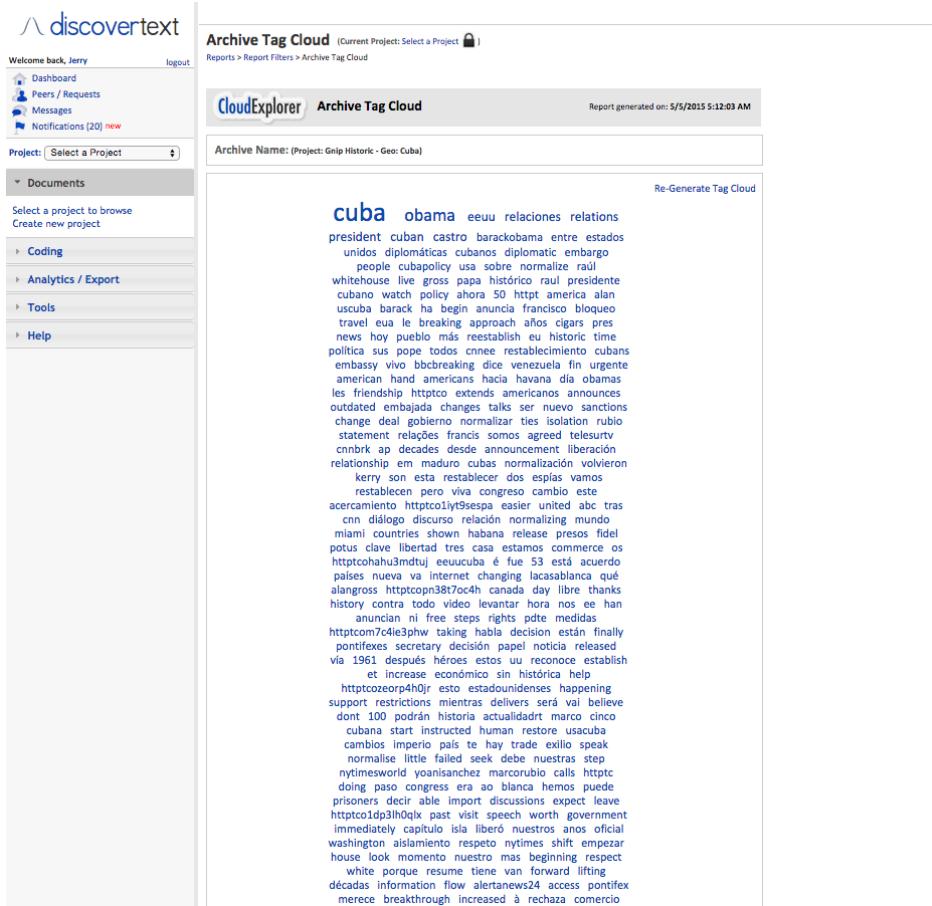
Data

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 application interface. The left sidebar contains a navigation menu with options like 'Dashboard', 'Peers / Requests', 'Messages', 'Notifications (20 new)', 'Project' (set to 'Grip Historic - Geo: Cuba'), 'Documents', 'Data Archives' (with sub-options for Has_Geo: Cuba 1 through 10), 'Buckets', 'Datasets', 'Coding', 'Analytics / Export', 'Tools', and 'Help'. The main area is titled 'Search and Browse Archive' and displays a list of 4,000 tweets from a project named 'Has_Geo: Cuba-5'. The tweets are listed in a scrollable table with columns for the user handle (@), the tweet text, and a small icon. The interface includes a header with 'Welcome back, Jerry' and 'Logout', and a footer with 'Advanced filters' and a page number '4,000 of 4,000'.



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. (<http://upload.wikimedia.org/wikipedia/commons/thumb/5/5e/Triangle.Centroid.svg/182px-Triangle.Centroid.svg.png>) 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 (<https://github.com/mbostock/d3/wiki/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).

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 projects, it really is the quality, quantity, relevance, and impact of 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.

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.

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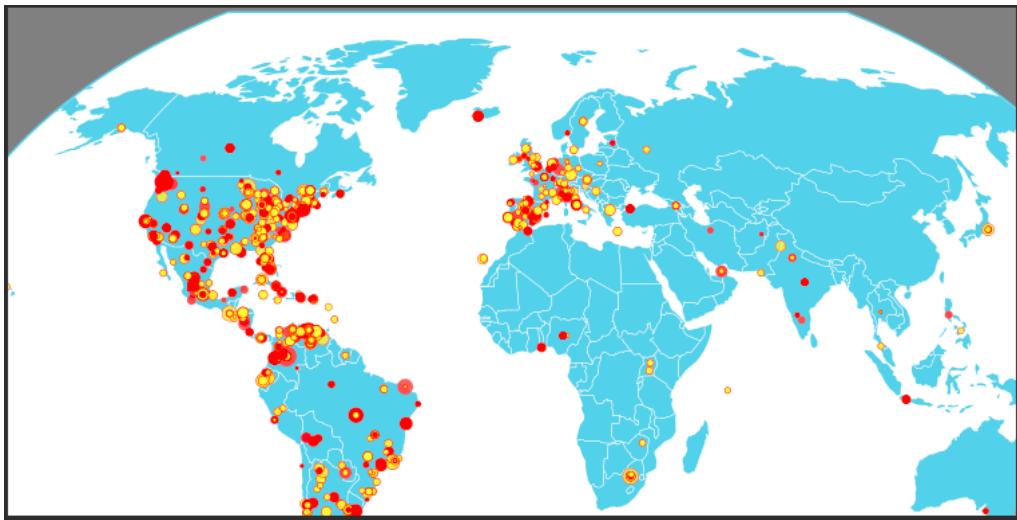
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9	RT @TheDailybe: RT @TheDailybe: Obama Realizes What 10 Presid	68	76	217						tag-search.twitter.com:20 http://twitter.com/range_cortez78/statuses/5450696901702451	pict.twitter.cc photo	http://pbs.								
10	RT @Leonardo_RT: @Leonardo_Padron: DÁ a histÁrico. USA y Cuba	97	451	1325						tag-search.twitter.com:20 http://twitter.com/cam_vallejo/statuses/54506968899174401										
11	RT @uselephan: RT @uselephant: "Hurry up with them cigars,	2092	2224							tag-search.twitter.com:20 http://twitter.com/67purple/statuses/54506969079955458	pict.twitter.cc photo	http://pbs.								
12	@andrescolonpr: #andrescolonpr y crees q no hay? He conocido syadsmins q eje	445	268							tag-search.twitter.com:20 http://twitter.com/jullor/statuses/5450696992033630										
13	RT @ManoloReveron: RT @ManoloReveron: Comienza la suponer la negociaciÁn de Cuba	1408	1987							tag-search.twitter.com:20 http://twitter.com/anniraul/statuses/54506971965628416										
14	Right-Wing Me! Right-Wing Media Lash Out After Obama Announces Deal With Ci	89	390							tag-search.twitter.com:20 http://twitter.com/Parcial2/statuses/54506973445812225										
15	@rmgev First @rmgev First book is Cuba; second is Turkey; third is Egypt ...	3421	1005							tag-search.twitter.com:20 http://twitter.com/rmgev/statuses/5450697174752460										
16	RT @mrgology: RT @mrgology: Raul Castro prepares to execute a	113	3147	2921						tag-search.twitter.com:20 http://twitter.com/CV_People/statuses/5450697237207040	pict.twitter.cc photo	http://pbs.								
17	Here's What Ha! Here's What Happened in Cuba Today, and Why You Should Care	1632	1930							tag-search.twitter.com:20 http://twitter.com/alaianamarla/statuses/5450697154626208										
18	RT @TeaPartyC: RT @TeaPartyCat: That awkward moment when Rep	5	296	495						tag-search.twitter.com:20 http://twitter.com/AtheistRaven/statuses/54506973861052416										
19	RT @HassNasa: RT @HassNasa: Cambio las relaciones con Cuba mie	18	2487	2729						tag-search.twitter.com:20 http://twitter.com/Analog_Zero/statuses/54506974213779456										
20	EU: Ofrecen ayuda a Cuba para resolver diferendo marÁ-timo co	328	760							tag-search.twitter.com:20 http://twitter.com/Parcial2/statuses/545069750825										
21	EU: Ofrecen ayuda a Cuba para resolver diferendo marÁ-timo co	157	869	6500	EEUU; Cuba					tag-search.twitter.com:20 http://twitter.com/infraillan/statuses/54506975157200	pict.twitter.cc photo	http://pbs.								
22	RT @monblonde: RT @monblonde: Theo Criticizing President Obam	45	3025	4104						tag-search.twitter.com:20 http://twitter.com/MTmaplynn2/statuses/5450697322437377										
23	EU: Ofrecen ayuda a EU: Ofrecen ayuda a PeñA para resolver diferendo marÁ-timo co	415	729							tag-search.twitter.com:20 http://twitter.com/rogr_7/statuses/5450697862420408										
24	RT @SAFWAMN: RT @SAFWAMM:USTAFAR: Nak jadi, bersahabat	118	303	569						tag-search.twitter.com:20 http://twitter.com/yanzana97/statuses/5450697862420408										
25	RT @Llojillaen: RT @LlojillaenTV: Viva Cuba! Viva Fidel! Tarde p	39	898	791						tag-search.twitter.com:20 http://twitter.com/Delgado_106/statuses/545069723117056										
26	RT @2405mabel: RT @2405mabel: poÁ-rica terrorista de Bush aho	2	850	1002						tag-search.twitter.com:20 http://twitter.com/proyecto_esp_b1/statuses/5450697756080472										
27	CUBA	12006	17							tag-search.twitter.com:20 http://twitter.com/b6handgra/RMT/statuses/54506980115169	pict.twitter.cc photo	http://pbs.								
28	EU: Ofrecen ayuda a PeñA para resolver diferendo marÁ-timo co	493	831							tag-search.twitter.com:20 http://twitter.com/llilovestaxa/statuses/54506981381435392										
29	EU: Ofrecen ayuda a EU: Ofrecen ayuda a PeñA para resolver diferendo marÁ-timo co	330	707							tag-search.twitter.com:20 http://twitter.com/mm90marcos/statuses/54506981381435392										
30	EU: Ofrecen ayuda a EU: Ofrecen ayuda a PeñA para resolver diferendo marÁ-timo co	415	729							tag-search.twitter.com:20 http://twitter.com/betomono5/statuses/5450697721025664										
31	RT @fidelcastrc: RT @fidelcastrc: Kerry espera ser el primer Secretar	6	1493	1484						tag-search.twitter.com:20 http://twitter.com/soosp_/statuses/5450697846765568										
32	RT @CNNMoney: RT @CNNMoney: Welcome to the Internet, Cuba. W	114	77	123						tag-search.twitter.com:20 http://twitter.com/b6handgra/RMT/statuses/54506980115169	pict.twitter.cc photo	http://pbs.								
33	RT @ElMonitor: RT @ElMonitor:1867. Obama anuncia el fin del aislamiento a Cuba	554	687	Venezuela						tag-search.twitter.com:20 http://twitter.com/xijesman30/statuses/54506978802327552	pict.twitter.cc photo	http://pbs.								
34	RT @Katherine: RT @Katherine: Let's go have fun in Cuba.	7	2633	2881						tag-search.twitter.com:20 http://twitter.com/llilovestaxa/statuses/5450698121769472	pict.twitter.cc photo	http://pbs.								
35	EU: Ofrecen ayuda a EU: Ofrecen ayuda a PeñA para resolver diferendo marÁ-timo co	361	885							tag-search.twitter.com:20 http://twitter.com/mm90marcos/statuses/54506981381435392										
36	RT @Bild111: RT @Bild111: @megynkelly @marthamacallum #K	1	516	777	KellyFife					tag-search.twitter.com:20 http://twitter.com/1776etsyRoss/statuses/5450698043396384										
37	Hey everyone!! Hey everyone!! We can go to Cuba! Screw that. We can't see "	616	1258	sal						tag-search.twitter.com:20 http://twitter.com/ajhenton/statuses/5450698061375744										
38	RT @yohanis: RT @yohanis: AlegÁ el dÁ D7 una column	49	4019	3611	GeneralAn					tag-search.twitter.com:20 http://twitter.com/longueira_2018/statuses/54506986075275266										
39	"@Reuters: U.S." @Reuters: U.S., Cuba restore ties after 50 years http://t.co/VrbC	159	71							tag-search.twitter.com:20 http://twitter.com/mfroogafall7/statuses/54506984552726528										
40	Alista EU nuevas regulaciones parauitar embargo a Cuba	860	37							tag-search.twitter.com:20 http://twitter.com/catharine_cecil/statuses/54506986267791361										
41	Alista EU nuevas regulaciones parauitar embargo a Cuba	622	63							tag-search.twitter.com:20 http://twitter.com/Pamardigal_7/statuses/5450698637549312										
42	RT @ml_magia: RT @ml_magia: Los cubanos quieren que el dÁl se	232	212	284						tag-search.twitter.com:20 http://twitter.com/digitalcarmona/statuses/54506980168903680										
43	Esa valma entre Esa valma entre gomina y cubanos no la decidim hoy, seguro qu	990	1813							tag-search.twitter.com:20 http://twitter.com/INGOSEMANUEL/statuses/54506986335289344										
44	Alista EU nuevas regulaciones parauitar embargo a Cuba	981	41							tag-search.twitter.com:20 http://twitter.com/duile_noma/statuses/5450698695622856										

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 twitter data is actually very messy. We spent equal or more time in data wrangling / analysis than in visualization.

Tools for semantic analysis are many, but we went with Semantria because they are strong supporters of visualization education and data research.

While Semantria is the industry leader, but dataset proved too unruly to handle in a limited amount of time. But great for exploration/derivative semantic measures. Had to get a virtual windows 8. Datafiles so big, excel would routinely crash. Crazy amount of cleaning had to be done just to do the semantic analysis. Limited api calls means, have to put serious thought into it.

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?

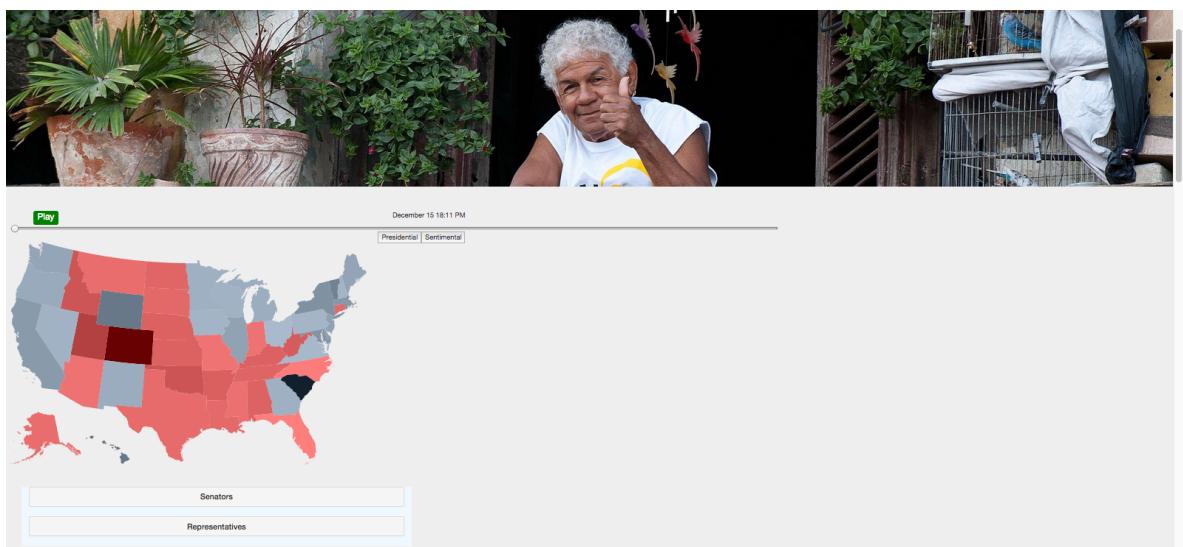
- ❖ For most of the project, we were unable to do proper data visualization during exploration because data set was orders of magnitude larger than anything we were prepared for, because most lacked reliable/easily usable geoData/.
- ❖ Main visualization for most of project was a slice of tweets mapped against US shaded to Obama Romney election results.
- ❖ We learned this was a massive dataset.
- ❖ Semantic Analysis is very very hard. Entities vs Documents, phrases, language detection (n-grams).
- ❖ Realization that a proper semantic analysis would not be feasible led to the pivot.

Design Evolution:

What are the different visualizations you considered? Justify the design decisions you made using the perceptual and design principles you learned in the course.

[Include pictures and use theory from book]

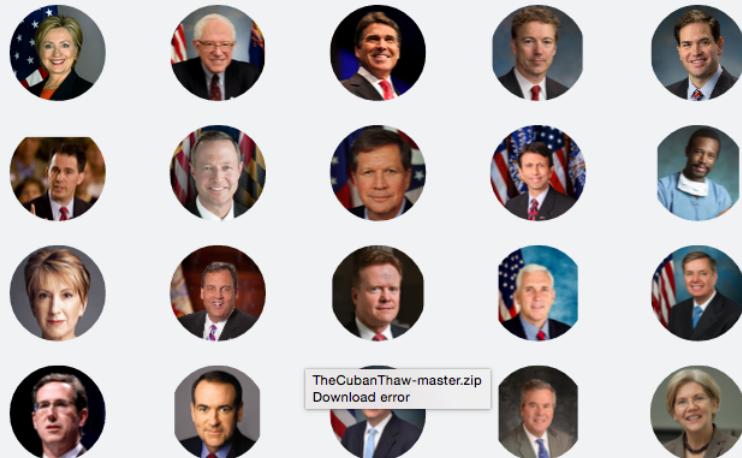
- ❖ struggles with color and maps
- ❖ deciding between greater honesty and greater utility/ greater aesthetics.
- ❖ deciding whether to aggregate and how to aggregate. Semantic analysis posed difficult aggregation questions. “If your visualization is correct at the aggregate but internally it is very volatile and wrong, is it a good visualization?” / “Meaning of average”
- ❖ “One page” website design vs traditional multi-page design in terms of story telling.
- ❖ Implementation: Describe the intent and functionality of the interactive visualizations you implemented. Provide clear and well-referenced images showing the key design and interaction elements.



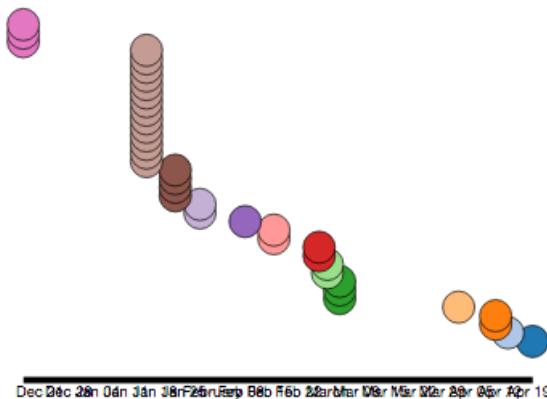
The Next President & Cuba



TheCubanThaw-master.zip
Download error



Thaw Events



Dec Dec 28n Jan 38r Feb 26n Mar 88b Feb 26b Mar 26r Mar 10r Mar 10r Apr 89r Apr 19

ID	Source Text	Summary	Detected Language	Detected Lemmatized	Document Sentiment	Phrase Intensity	Phrase Neglect	Phrase Semantic	Phrase Similarity	Phrase Suggested	Entity	Entity Type	Entity Neglect	Entity Semantic	Entity Similarity	Entity Evidence
5156	4716-795- suffered enough! Let's move int	Cuba. The civilians have	English	5	0.102 neutral	EndTheEmbargo	0.4	positive	n't make	Cuba	Place	1	positive	7		
5157	4537-92ae- Cuba and help oppress some dissidents!!	Oppress	English	15	-0.392 negative	oppress	-0.392	negative	n't Obama	Cuba	Place	Place	negative	7		
5158	48ae-9cf- Love this move by Trump for Cuba to make progress.	progress	English	8	0.1659131 neutral	progress	0.1659131	neutral	Cuba	Place	Place	0.4147426	neutral	7		
5159	4209-932- US and Cuba have been interesting to	interesting	English	16	-0.0364242 neutral	interesting	0.0364242	neutral	Cuba	Place	Place	-0.0364242	neutral	7		
5160	4557-9322- Kim Jong-un and Castro brothers. How pathetic!	pathetic	English	16	-0.0003045 neutral	good	0.5	positive	Cuba	Place	Place	-0.0003045	neutral	7		
5161	4064-914- NormalizationOfCuba Diplomacy at its best	NormalizationOfCuba	English	4	0.49 positive	best	0.49	positive	NormalizationOfCu	Person	Person	0.49	neutral	7		
5162	4251-90aa- the people of Cuba will have better lives because of this,	Obama talk about Cuba	English	18	0.06732 neutral	Hopefully	0.28196	positive	Cuba	Place	Place	0.50245	positive	7		
5163	48z-8ca- Happy Hannukah to Alan and Judy Gross!! Cuba	Judy Gross!! Cuba..	English	3	0.2 neutral	Happy	0.2	neutral	Alan	Person	Person	0.5	neutral	7		
5164	47ea-aed- still illegal and exciting.	make it to Cuba back	English	15	-0.1152 negative	still	-0.3996	negative	n't make	Cuba	Place	-0.132	neutral	7		
5165	4660-e11- cuba...this is a mean photo opp and thumb in the eye	cuba...this is a mean	English	18	-0.323394 negative	no	-0.8296	negative	photo	Cuba	Place	-0.1148	neutral	7		
5166	4716-795- Cuban Americans remember why we are mad at Cuban Americans!	Cuban Americans!	English	12	0.00 neutral	mad	-0.372204	negative	remember	Cuba	Place	-0.807788	negative	7		
5167	4ab0-8786- Now this is sick! Never like this? A Ray of Hope! Cuba	Never like this?	English	12	0.00 neutral	Huge	0.08	neutral	Never like	Cuba	Place	Company	0.5	neutral	7	
5168	4fb0-818b- (Till now, only European ones have worked there).	(Till now,	English	16	0.0616354 neutral	only	0.0616354	neutral	European ones	Cuba	Place	0.1540884	neutral	7		
5169	451a-e41- Cuba's Human rights record??	telling me you're not	English	10	0.446032 positive	human rights	0.446032	positive	telling	Cuba	Place	1.11508	positive	7		
5170	4f63-9115- Many pluses there including public health,	policy on Cuba	English	12	0.160 neutral	So	0.75	positive	Many pluses	Cuba	Place	-0.034	neutral	7		
5171	42ce-b31d- Not quite such good news for VladimirPutin	Cuba ties are a win for	English	15	-0.07069 neutral	win	0.5239821	positive	US	Place	-0.024241	neutral	7			
5172	421b-ae0f- Hispanic voters in Miami have been able to	window dressing	English	15	-0.5 negative	idiotic	-0.6	negative	votes	Cuba	Place	-0.5	negative	7		
5173	421b-ae0f- Cuban Americans in Miami have been able to	Window dressing	English	15	-0.5 negative	particular	-0.5	negative	legally go	Cuba	Place	-0.5	negative	7		
5174	428f-ab5c- CartoonsAgainstCrime in 1993, my strongest	Founder	English	11	0.0384535 neutral	strongest	0.196	neutral	particular	Cuba	Place	0.4	neutral	7		
5175	428f-ab5c- CartoonsAgainstCrime in 1993, my strongest	Founder	English	11	0.0384535 neutral	Crime	-0.2406394	negative	strongest	Cuba	Place	-0.057993	neutral	7		
5176	4ee1-bf91- policy pivot. In real life, it was Ben Rhodes	who orchestrated the	English	15	0.106 neutral	In	0.212	neutral	real life	Leo	Person	0.106	neutral	7		
5177	4ee1-bf91- policy pivot. In real life, it was Ben Rhodes	who orchestrated the	English	15	0.106 neutral	real life	0.212	neutral	real life	Ben Rhodes	Person	0.106	neutral	7		
5178	4ec6-d011- on the New US policy on CubaPolicy	President of Haiti	English	12	0.5880001 positive	thanked	0.5880001	positive	real life	Senator	Job Title	0.49	neutral	7		
5179	4709-894- Normalizing and Endorse Cuba. 3. Shortage solved!	normalized via Z.	English	5	0.00 neutral	Embrace	0.16	neutral	real life	Cuba	Place	1	positive	7		
5180	4e20-b271- Zimbabwe and Egypt Regimes that use torture are bad	isolated as China	English	18	-0.023413 negative	isolated	-0.6	negative	real life	Zimbabwe	Place	-0.336455	neutral	7		
5181	4e20-b271- Zimbabwe and Egypt Regimes that use torture are bad	isolated as China	English	18	-0.023413 negative	bad	-0.6	negative	isolated	Egypt	Place	-0.336455	neutral	7		
5182	4e20-b271- Zimbabwe and Egypt! Regimes that use torture are bad	isolated as China	English	18	-0.023413 negative	torture	-0.49	negative	isolated	Zimbabwe	Place	-0.336455	neutral	7		
5183	4e20-b271- Zimbabwe and Egypt! Regimes that use torture are bad	isolated as China	English	18	-0.023413 negative	Just look	0.080635	neutral	violations	Egypt	Place	-0.336455	neutral	7		
5184	47fc-849c- relationships with Cuba after all the human rights	would try to normalize	English	19	-0.12 negative	Just look	-0.24 negative	negative	violations	Cuba	Place	-0.3	neutral	7		
5185	47fc-849c- relationships with Cuba after all the human rights	would try to normalize	English	19	-0.12 negative	n't believe	-0.1	neutral	violations	Ben Marco Rubio	Person	0.4	neutral	7		
5186	47fc-849c- improved lives and jobs for everyone. So fucking	Human rights	English	9	0.0430001 neutral	impassioned	0.16	neutral	n't believe	Obama	Person	-0.199831	neutral	7		
5187	4755-6e67- Obama has a long history of codding tyrants	tyrants	English	5	-0.100821 negative	tyrants	-0.6	negative	tyrants	Mr. Gross	Person	-0.533334	negative	7		
5188	402e-846c- doing nothing more than reaching out to Jewish peop	to rot away in a Cuban jail	English	16	-0.533334 negative	rot	-0.6	negative	to rot away in a Cuban jail	Iran	Place	-0.6811	negative	7		
5189	412d-8565- No. Korea All terrorists States. We g	opens relations with	English	6	-0.27244 neutral	terrorists	-0.27244	negative	terrorists	Cuba	Place	-0.8811	negative	7		
5190	412d-8565- No. Korea All terrorists States. We g	opens relations with	English	6	-0.27244 neutral	restoration	0.4042857	positive	restoration	AP	Company	0.267549	neutral	7		
5191	49cf-8bb8- of diplomatic ties with US, says differences remain.	Raul Castro welcomes	English	8	0.2675449 positive	diplomatic ties	0.130804	neutral	diplomatic ties	Cuba	Place	0.267549	neutral	7		
5192	49cf-8bb8- of diplomatic ties with US, says differences remain.	Raul Castro welcomes	English	8	0.2675449 positive	negotiator	-0.196	negative	negotiator	Raul Castro	Person	0.267549	neutral	7		
5193	49cf-8bb8- of diplomatic ties with US, says differences remain.	Raul Castro welcomes	English	8	0.2675449 positive	president	-0.2722	positive	president	US	Place	0.267549	neutral	7		
5194	49cf-8bb8- of diplomatic ties with US, says differences remain.	Raul Castro welcomes	English	8	0.2675449 positive	worst	-0.196	negative	worst	president	Job Title	-0.0868937	neutral	7		
5195	471a-9e6d- negotiator we have ever had." Cuba, his home, did not	president has to be	English	19	-0.0347575 neutral	freedom	0.2722	positive	freedom	Cuba	Place	-0.0868937	neutral	7		
5196	471a-9e6d- negotiator we have ever had." Cuba, his home, did not	president has to be	English	19	-0.0347575 neutral	worst	-0.196	negative	worst	Cuba	Place	-0.0868937	neutral	7		

Evaluation:

What did you learn about the data by using your visualizations? How did you answer your questions? How well does your visualization work, and how could you further improve it?

The US embargo of cuba was a very big deal to people in Latin America and Europe. The Thaw crossed into the mainstream conversation with many ordinary people commenting on it.. Also, even though Twitter skews young, Florida still erupted with activity indicating a young cuban population is politically engaged which could prove dangerous to some politicians.

We had no idea Venezuela's Twitter has such an extensive presence. as much as it did. Venezuela has been Cuba's closest ally over last 10 years. That ended with death of Hugo Chavez and now the collapse of oil which Venezuela's economy depends on as one of the largest exporters of petroleum in the world.

We chose this dataset because we felt strongly that our dataset is truly a significant part of history. Not only did it capture a historical detente, but it did 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 very that man If you truly understand this dataset, you can know the minds of hundreds of thousands of people in the US and around the world.

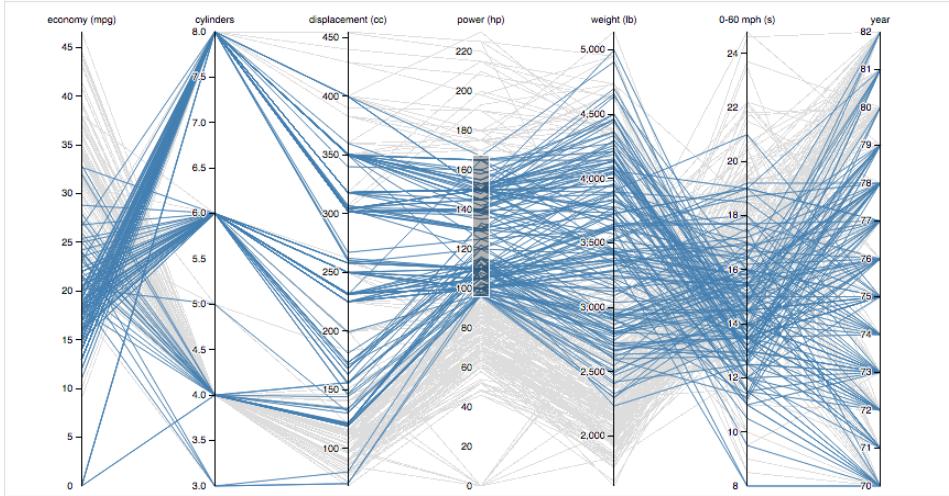
Improvements:

- 1) Take 2-3 months and dive extremely deeply into semantic analysis (not recommended, there are better ways)

- 2) 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.
- 3) We could have tweets of a certain hashtag increase the proportion of that color in a countries color, thus country takes on the color of most popular hashtag

Our main visualization for most of the project. Map of the US with a small subset of 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.

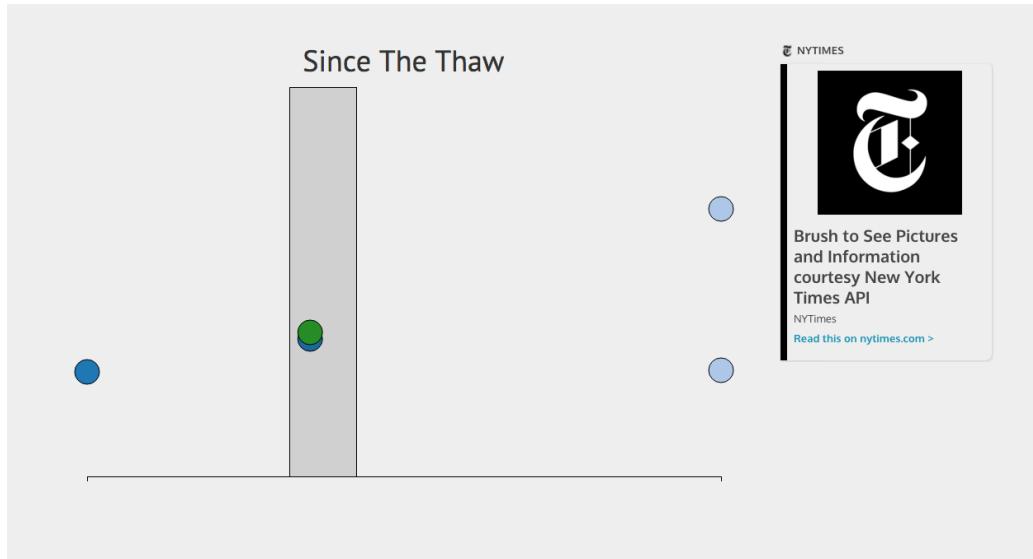
Parallel Coordinates



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

[Open in a new window.](#)

Discussed with TA about turning visualization of presidential candidates into a Parallel Coord vis, but while technically interesting and visually complex, we feel that this is too advanced for our expected users and their use cases. It is neither the most intuitive solution nor the most promising of insight 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



Purpose of this visualization was to communicate to the user the immediate consequences of the Thaw through events happening in the news. This brush queries the NYTimes for articles related to Cuba between the brush's extent.

The Next President & Cuba



[For | Against]

The Cuban Thaw Tweet Map The Next President & Cuba Since The Thaw

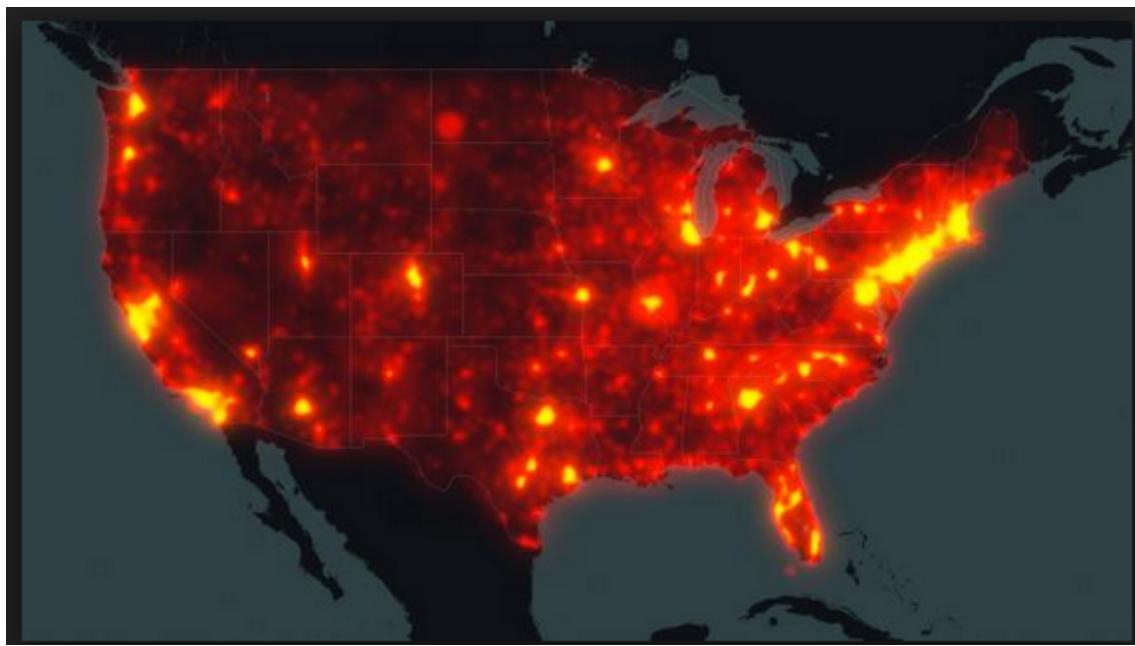
Play December 15 18:11 PM

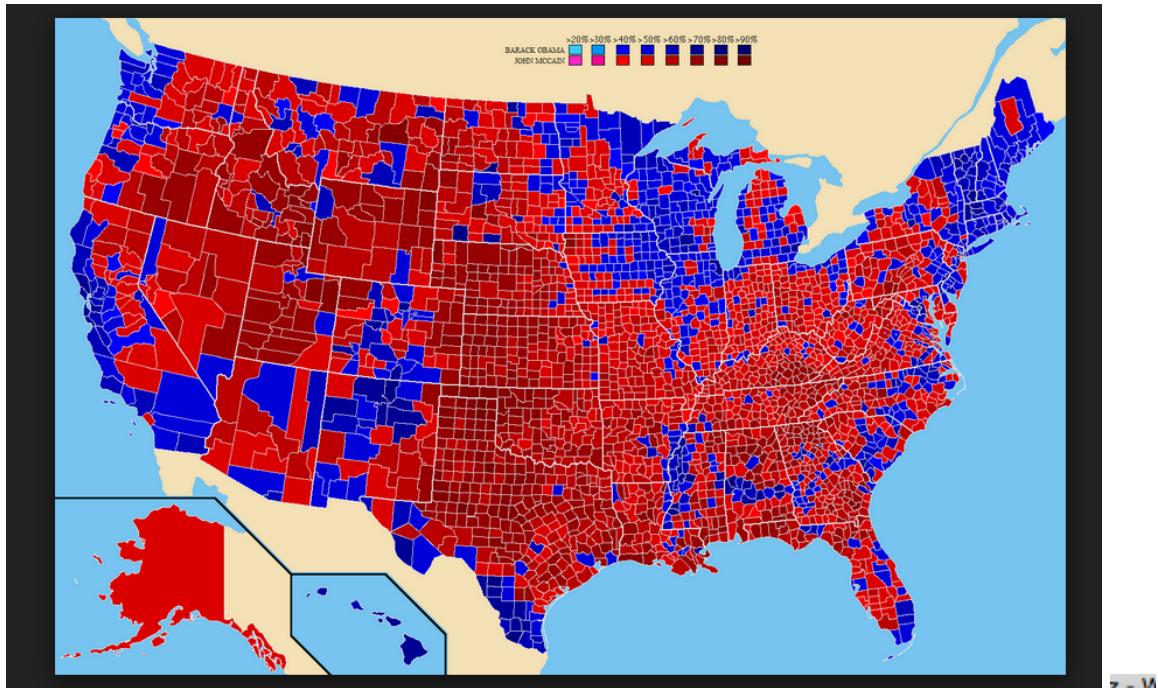
Presidential Sentimental

Senators

Representatives

This interface allows users to explore political data related to the 2016 US election, specifically focusing on support for Cuba. It includes a map of the US showing state-level sentiment, a grid of candidate portraits, and sections for senators and representatives.





TopMeta Discovery

x

Top values for: country_code:

1 of 6 

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

Welcome back, Jerry [Logout](#)

[Dashboard](#) [Peers / Requests](#) [Messages](#) [Notifications \(20\) new](#)

Project: [Gnip Historic - Geo: Cuba]

Search and Browse Archive [Has_Geo_Cuba-5 \(Archive\)](#)

Showng 59,976 to 100,000 of 100,000 total

Add to Bucket: New | Existing | Selected

Advanced Filters

4,000 of 4,000

Gnip Historic - Geo: Cuba

- **Documents**
- **Gnip Historic - Geo: Cuba**
 - Data Archives
 - Has_Geo_Cuba
 - Has_Geo_Cuba-10
 - Has_Geo_Cuba-11
 - Has_Geo_Cuba-12
 - Has_Geo_Cuba-13
 - Has_Geo_Cuba-3
 - Has_Geo_Cuba-4
 - Has_Geo_Cuba-5
 - Has_Geo_Cuba-6
 - Has_Geo_Cuba-7
 - Has_Geo_Cuba-8
 - Has_Geo_Cuba-9
 - Buckets
 - Databases
- Coding
- Analytics / Export
- Tools
- Help

RT @arzE: If two Rolex can live happily next to each other, why can't the US & Cuba?? <http://t.c...>

RT @eliaspino Rubio Warns Congress Will Resist Cuba Policy <http://t.co/597cnpAsZ> via @NYTPolitics

Presidente @NicolasMaduro destaca "valentia" de Obama para restablecer relaciones con Cuba <http://t.c...>

@marcorubius you speak very well sir, I disagree with your opinion on #CubaPolicy but I respect it.

Raúl Castro confirma que los tres agentes cubanos ya están en La Habana <http://t.co/DLYNlxnPxn>

Curiosidades #EEUU #Cuba <http://t.co/6WnBA6VoQC>

Para enterarse del acontecimiento histórico del restablecimiento de relaciones entre Cuba y EUA, sig...

@joshrogin @Jakettapper the inclusion of Cuba on that list has long been debatable.

RT @Palestina: Terminará embargo después de medio siglo de bloqueo yanqui contra Cuba? Ojalá! Y el b...

@BarackObama TAKING OFF MY HAT FOR OPENING RELATIONS WITH CUBA & @@Pontifex GOD BLESS YOU !!ps.f...

RT @ActualidadRT: #Obama anunció que pedirá al Congreso estadounidense levantar el bloqueo de Cuba h...

RT @ltvnews: Pope Francis congratulates US and Cuba on agreement. <http://t.co/RL3YMI1AS0>

Say what you want about Cuba...but Lena Olin in Unbearable Lightness of Being > Lena Olin in Hava...

RT @arzE: if two Rolex can live happily next to each other, why can't the US & Cuba?? <http://t.c...>

RT @marclamonthill: The Left must demand the continued protection of our political prisoners by the ...

RT @ultimosegundo: Espião libertado forneceu informações cruciais para processos contra cubanos <http://t.c...>

RT @MauroMura11: La UDI cuando supo lo de EEUU y Cuba. <http://t.co/RkgLkThiGo>

RT @WRadioColombia: #AlAire análisis con Claudia Palacios @claudiapcn, noticia del dia: se acercan ...

RT @WhiteHouse: President Obama speaks with President Raúl Castro of Cuba before announcing his #Cub...

Alegra al Papa que Cuba y EU superaran dificultades: El Pontífice dijo estar "vivamente" complacido...

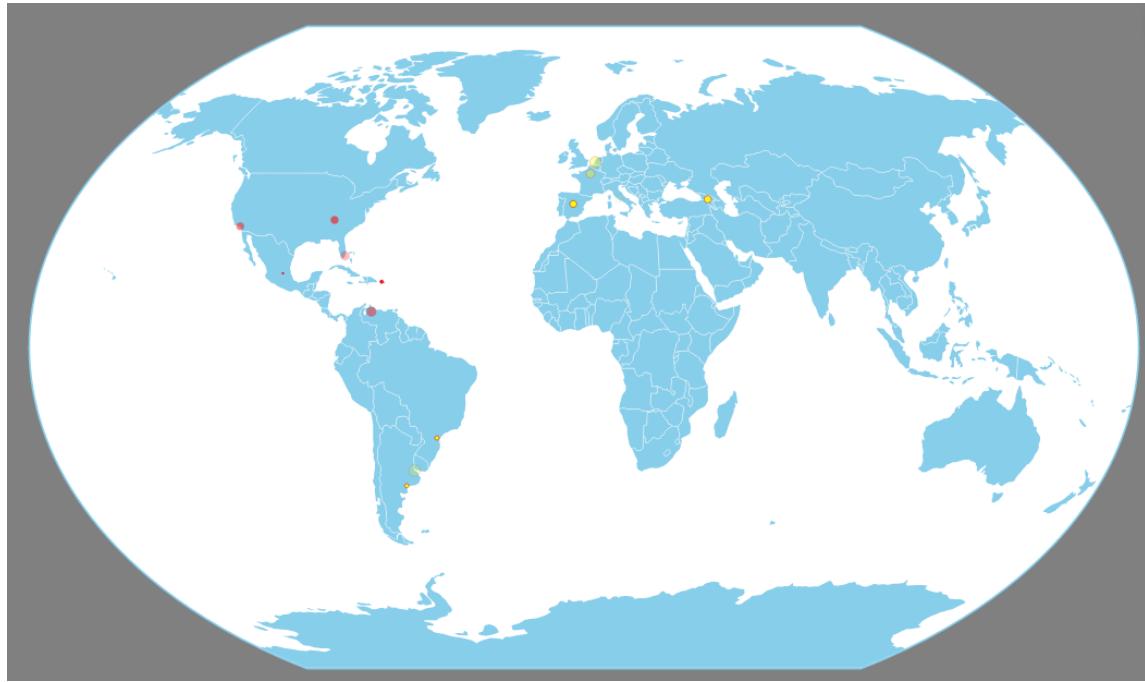
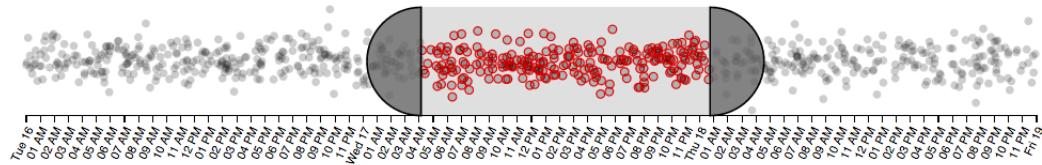
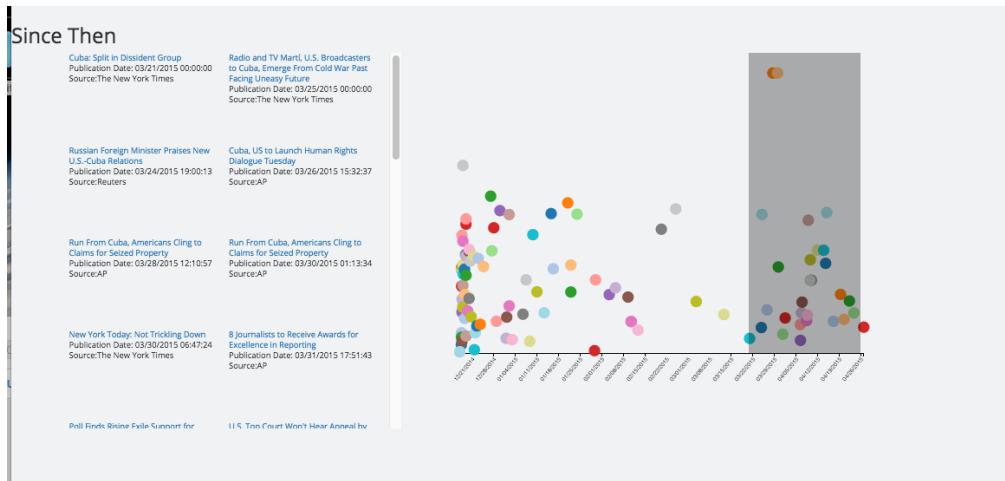
No puede con los tweets <<Vla Cuba U.S.A>> JAJAJAJAUAJAIAJAIAJA

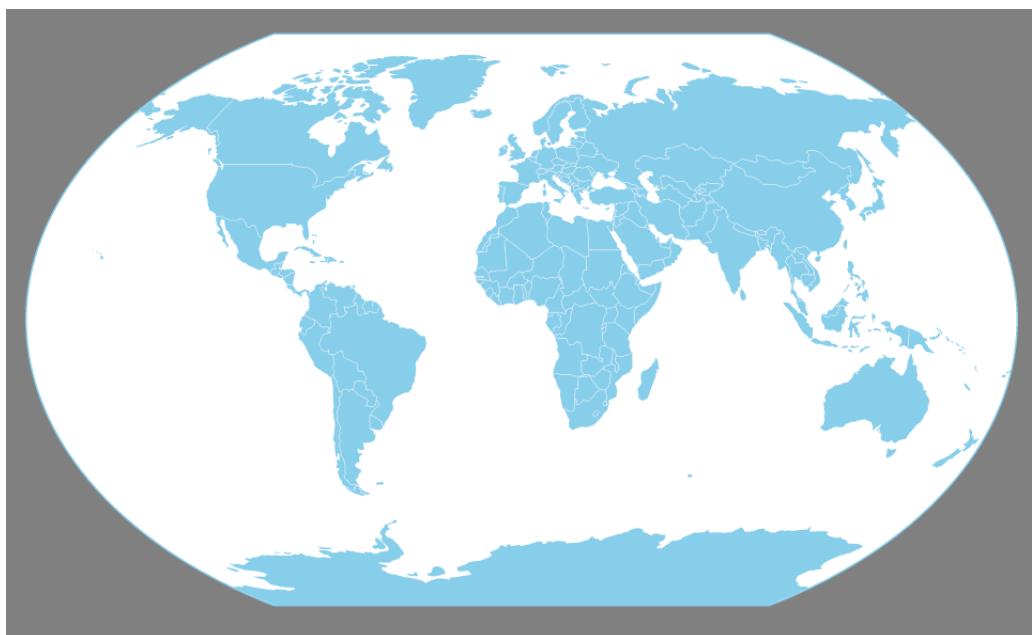
RT @arzE: if two Rolex can live happily next to each other, why can't the US & Cuba?? <http://t.c...>

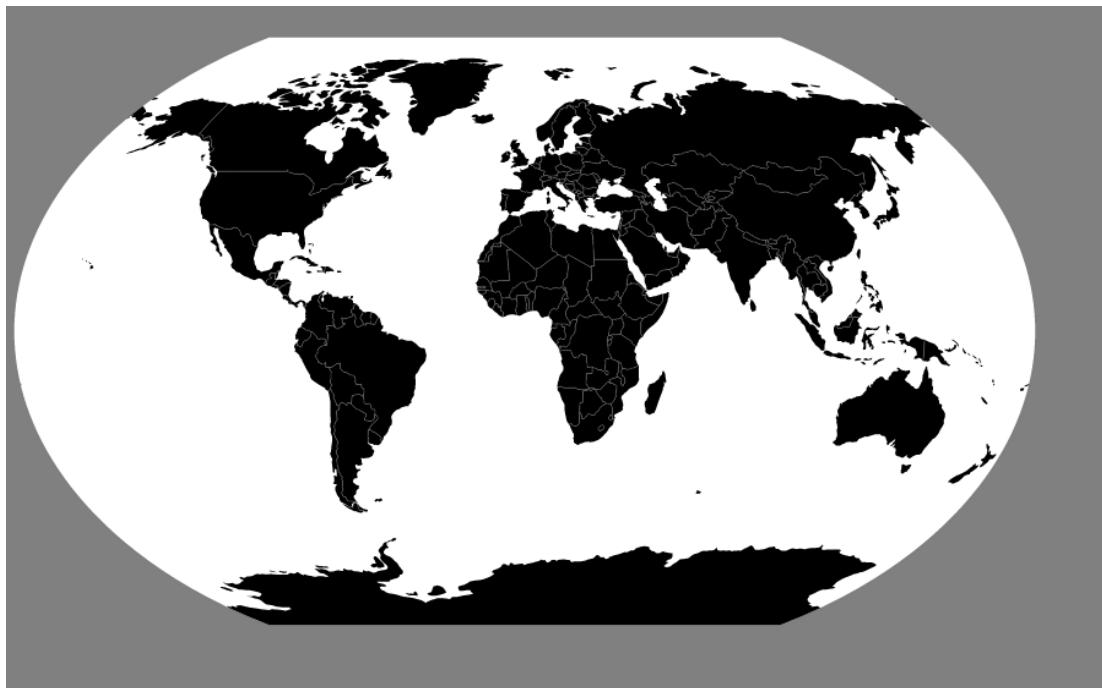
Q dirán ahora los Robolucionarios Vzolanos?? Presidentes d Cuba y Estados Unidos acuerdan normalizar ...

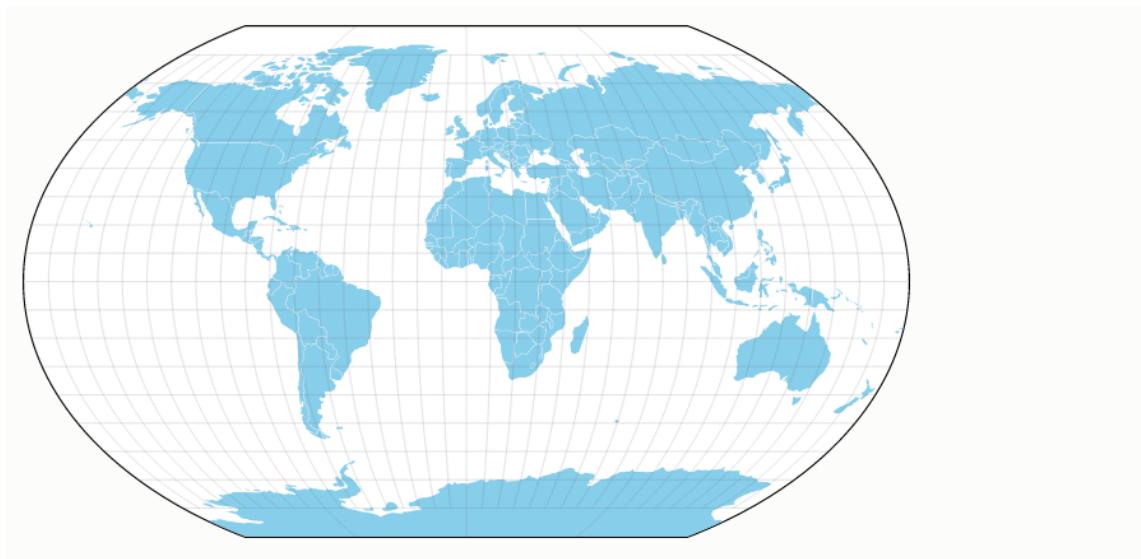
RT @CaracolRadio: Presidente Juan Manuel Santos se manifiesta esperanzado por el diálogo entre EEUU ...

RT @sinderbrand: WashPost Cuba heds before and after, 53 years apart. <http://t.co/TiuVX89IW>









Not Safe Anymore

Visualizing Web Attacks over a 24-hour period for 2014 Tax Day

This application allows you to view network attack data that was collected by Alarma's firewalls. It shows the number of attacks originating from each city, based upon the filters that have been applied. That data can be filtered by hour of the day, country, or network (ISP), using the controls at the bottom of the page. By default, all data is displayed.

