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When the City Meets the Citizen

FoodMood: Measuring Global Food Sentiment One Tweet at a Time

Natalie Dixon, Bruno Jakić, Roderik Lagerweij, Mark Mooij, Ekaterina Yudin
Affect Lab, Ai Applied, Ai Applied, Ai Applied, Affect Lab
natalie@affectlab.org, bruno@ai applied.nl, roderiklagerweij@gmail.com, mark@ai applied.nl, katy@affectlab.org

Abstract

Do Happy Meals really make us happy? Do salads make us blue? Is cake our comfort? FoodMood is an interactive data visualisation project that gives citizens a rare opportunity to engage and reflect, acknowledge, and understand the connection between emotion, obesity and food. The project explores the opportunities presented by the data sharing world of today's cities using global English language tweets about food coupled with sentiment analysis. It aims to gain a better understanding of global food consumption patterns and its impact on the daily emotional well being of people against the backdrop of country data such as Gross Domestic Product (GDP) and obesity levels. A key finding is that tweets can be used to find a relationship between certain foods, food sentiment and obesity levels in countries. Overall FoodMood shows a majority positive sentiment towards food. Other findings, although constantly evolving, indicate trends such as: globally meat enjoys a high sentiment rating and is often tweeted about; fast food companies dominate the food consumption landscapes of most countries' tweets although not all of them enjoy equal sentiment ratings across countries. Ultimately, FoodMood reveals a hidden layer of meaningful digital, social, and cultural data that provide a basis for further analysis.

Introduction

In recent years, food has become the rising star of public debate. Documentaries such as *Food Inc*, *Fast Food Nation*, *King Corn* and *Supersize Me*, have brought food issues into the realm of popular culture and into sharp focus for many urbanites. With unprecedented focus on the subject of food worldwide, citizens have never been more aware of what they are eating and the effect it has on their bodies. Yet, 2.3 billion people will be classified overweight and over 700 million as obese by 2015 according to the World Health Organisation (2011). Arguably, government and citizen interest, consumer focus and the food industry itself are at an enormous tipping point. FoodMood is a data visualization tool that explores the opportunities presented by the data-sharing world of today's cities using global English-language tweets about food coupled with sentiment analysis. It aims to gain a better understanding of global food consumption patterns and its impact on the daily emotional well-being of people against the backdrop of country data such as Gross Domestic Product (GDP) and obesity levels.

By engaging citizens with their own data about food, FoodMood comes at a highly relevant time for reflection and self-awareness. As a search interface that provides an engaging means of exploration, FoodMood utilizes and visualizes digital social data to lend important insights into citizen behaviour, and urban living patterns and practices. The end user experience is meant to be an immersive interaction with the data in both a qualitative and statistical way. Users can perform various search navigations such as country and food comparisons, sorting by emotion or by tweet quantity and zooming down into the individual tweets. The ability to see data at both a macro-level and micro-level gives users both a birds-eye-view of certain trends as well as a deeper interactive experience.

Food consumption – a naturally social phenomenon – and its reflection in the emotional social web of Twitter becomes a lens to reveal patterns in society. One of the questions FoodMood addresses the growing problem of obesity globally can be reflected with the use this tool. Specifically can these obesity-contributing foods be categorized and quantified? With the affordance of information visualisation tools, that help amplify cognition, researchers and users can gain a better understanding of millions of processes and events as well as uncover patterns that were "hidden" in mountains of facts, numbers, words and percentages (Card 1999). Beyond helping discover new understandings amidst a profoundly complicated world where too much data creates a problem of scaling, a great visualization can help create a shared view of a situation and align people on needed action.

Method

Data Processing

The basic structure of FoodMood's architecture is depicted in Fig. 1. The system continuously gathers live data related to recent food consumption from Twitter by querying the standard Twitter API with terms such as "for dinner", "for lunch", "for breakfast", "I ate" and "I'm eating." The gathered tweets are analyzed to determine whether they contain food types, and if a certain tweet is determined to hold a food item the tweet is processed further. For each relevant tweet the FoodMood system consults the geolocation component to determine the location of the Twitter user. If the user's location, abstracted to the level of a country, can be acquired the tweet is sent to the Sentiment Analysis system to determine the overall sentiment orientation of the tweet. A combination of the tweet, the recognized food, the Twitter user location, the Twitter user identity, and the sentiment orientation is stored in the database.

In addition to live data from Twitter, the FoodMood system uses static data from CIA World Factbook (CIA) and the World Health Organization (WHO) for a country's GDP per capita and obesity levels, respectively. This information is obtained from the websites of those organizations, and further processed in order to achieve uniformity of country naming between the static data and the data retrieved by geolocation. A total of 160 countries are present in the database with the annotated GDP per capita and obesity levels.

Upon request, database information from Twitter and the additional country information are combined, processed and provided to the front-end for visualization.

Food Detection

Considering the number of possible foodstuffs (estimated at 10s or 100s of thousands), it is unfeasible to manually compile a list of all the possible foods and use simple pattern matching in order to extract the food items from the tweets. A limited, manually compiled list, would severely limit the expressive power on the side of emotion, as many foodstuffs would be disregarded or grouped under more generic descriptors, which we expected to give a bland landscape with regard to the emotion: while the sentiments associated with "fried chicken", "grilled honey chicken" and just "chicken" could be wildly different, grouping all of them under "chicken" would result into a major loss of fidelity with regard to the sentiment. It was therefore

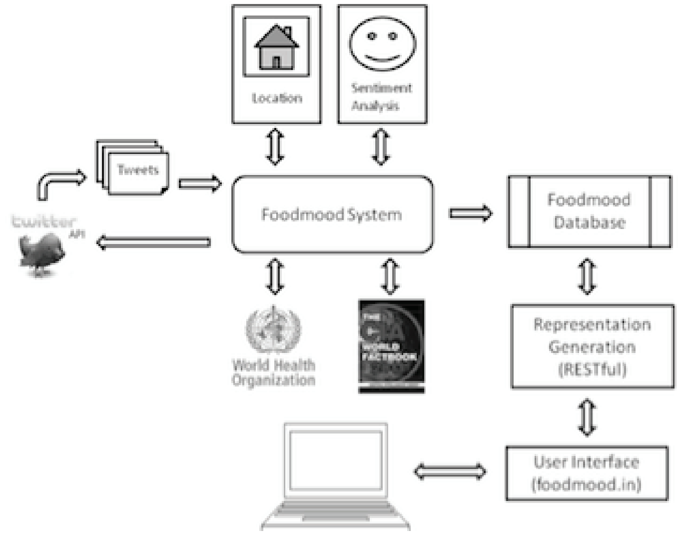

Figure 1. FoodMood Architecture

necessary to devise a system that could extract with a high level of precision the foodstuffs from the tweets, including foodstuff-related adjectives and colloquial language while rejecting qualitative adjectives and everything that wasn't a food item.

The Pointwise Mutual Information (PMI)[1] measure was used to achieve our goal of precise food item extraction from plain text constructs. The approach works as follows: first, the retrieved tweet is lower-cased and filtered from all non-alphabetic characters and the Twitter search terms, with the exception of spaces. Ngrams[2] are then created of the remaining words, of the 0th, 1st, 2nd and the 3rd order. The 3rd-order is being used as the upper limit, as previous observation has indicated that it is very rare that a food item has more than three qualitative adjectives describing it. Subsequently, the created Ngrams are being used with a directly food related search term on the Bing search engine in order to retrieve the number of search results for this combination. Food related search term and combination used is "I ate <Ngram> for", while the generated Ngrams are used in a descending order (e.g. "grilled chicken" before "chicken"). Using this search term, we require the Ngram to be edible - literally or colloquially. The number of search results for the combination of the Ngram and the search term, and the separate number of search results for the Ngram and the search term respectively are used as the elements for the calculation of the PMI, the value of which is considered as the score indicator for Ngram being a food item. It is, however, not enough just to calculate the PMI score of the Ngram in the context of the food. The process is repeated with a number of search terms that are intended to calculate the PMI scores for the Ngram in the context of *not* being a food item, such as "I went to <Ngram>". If the

[1] http://en.wikipedia.org/wiki/Pointwise_mutual_information
[2] http://en.wikipedia.org/wiki/Hidden_Markov_model

PMI score of the Ngram in the context of food is higher than the PMI score of the Ngram in the context of *not* being food, the Ngram is considered likely to be food. In order to increase the accuracy of the system, in such a case the Ngram itself is being queried using the Bing API, and the text content of short descriptions of the first 10 search results from Bing is analyzed for food related terms such as "recipe" or "restaurant." If those terms are present, the Ngram is definitely considered to be a food item, and it is added to a cache of food items. In this case, all Ngrams which are subsets of the classified Ngram are discarded from further analysis, while the food-item Ngram is added to a cache of food items, against which future tweets are first compared to optimize for speed. In the case that the Ngram has been found not to be a food item, it is added to the cache of non-food items, against which future tweets are compared to optimize for speed. In this way it is possible to extract correctly the food items consisting of edible foods or colloquially known food terms such as "McDonald's", including valid adjectives, while excluding non-food items and qualitative food adjectives. After experimenting with this automatic detection system for three days a total of 3,668 food items had been detected, with a total of 38,712 non-food items. Upon the manual inspection and annotation of the food item list and non-food item list it was determined that the system performs with a 96% accuracy. When the system mistakes a food item for a non-food item or vice versa, the item in question is usually a very commonly used word (e.g "night") or food item (e.g "chicken"). This is consistent with what we would expect from the statistical approach of determining foodstuff. To alleviate this problem the generated lists are periodically inspected and corrected manually.

Geo Location

Determining the geographic location from where the food related-tweet is made is accomplished in one of two ways. The first is to use the geotag assigned to the tweet. This tag describes the latitude and longitude coordinates from where the tweet is made. If, however, the tweet is not geotagged, it is assumed that the tweet is made from the location that the user has provided in their Twitter profile. In the case that the user hasn't provided a location, the tweet is disregarded. In practice, only a small percentage of tweets are geotagged, but most users do provide a location in their profile.

As people often misspell locations, use abbreviations, or report non-existing locations, the resulting list contains many locations from which the name of the relevant country cannot be (directly) inferred. Also, Twitter users tend to report their location with varying levels of specificity, while we are generally only interested in the name of its country. In order to filter out the non-existing locations and resolve this many-to-one mapping, the Microsoft Bing Maps service was used.

Microsoft's Bing Maps is an online service that allows for querying the name of a location. Given this input location, the service will return a full description of one or more locations that can be mapped to this name. Among other details, these descriptions include the name of the country and a confidence level the retrieved location belongs to the input query. The Twitter API was used to return the location a user has reported in his or her profile. Non-alphanumerical characters are filtered out from this string, as the Bing search is sensitive to non-relevant information. The Bing engine was queried with the resulting string, and depending on the confidence level Bing supplies the system will decide whether or not to assign a country to the retrieved Twitter location. If the returned confidence level is *high*, a partial string matching check is applied to verify that indeed the provided Twitter location and the returned location from Bing refer to the same geographic entity. As results from Bing are frequently assigned a *high* confidence level, this additional verification step filters out many false candidates. Results with *medium* and *low* confidence levels are ignored, as experimenting showed that this would lead to many false positives. If no country can be assigned to the tweet, the tweet is disregarded. To optimize for speed and to limit the number of requests made to the Twitter and Bing API, the processed location from Twitter users and retrieved location derived from Bing requests, were both cached.

The described approach has several advantages. First, the Bing Maps service is able to map names of cities, streets, points of interest to a geographic location. It thus provides the name of a country, even if this information cannot literally be found in the extracted location. Second, it normalizes the naming of locations, i.e. countries will be referred to with a single naming convention. This is necessary to combine their statistics on food and sentiment. Thirdly, the Bing Maps service has the ability to map geographic coordinates to a location, if a tweet is geotagged with latitude and longitude coordinates. Of all Tweets provided to the geolocation system 74% are kept and annotated while 26% are discarded for reasons described above.

Sentiment Analysis

Sentiment Analysis is used to extract sentiment from the tweets about food. Sentiment analysis is an application of natural language processing, computational linguistics, and text analytics to identify and extract subjective information from different source materials. One of the most basic tasks of the sentiment analysis tool is to determine the overall tonality and classify the polarity of a given text to indicate whether a sentence or a feature of a document is positive, negative, or neutral. Using a method similar to Go et al for an accurate Sentiment Analysis Classifier for Twitter, the classifier was trained on one million tweets in the food domain (2009). In the research by Go et al accuracies of 83% are achieved. Go et al describes that it is not really possible to train a classifier to perform better than 85% accuracy for Sentiment Analysis tasks, as tests have shown that human annotators cannot agree on the right classification in about 15% of the cases (2009). FoodMood reached similar accuracy levels within the food domain as the linguistic form of the source materials was the same (tweets about food).

By using the Bayesian Sentiment classifier the exact probability that the tweet is positive (or negative) is returned to the system. We use the positive Bayesian chance as a "happiness percentage".

Visualisation

The beta version of FoodMood can be found at http://www.foodmood.in, and is depicted in Fig2. One of the affordances of a treemap visualisation is being able to represent a vast number of entities (foodstuffs) and simultaneously view the prominence (number of tweets) and associated emotion of those in a hierarchical way. This technique is also credited with efficient use of space (Card, MacKinlay and Schneiderman 2009). The use of a treemap as the visual structure of FoodMood enables users to explore emotion in an interactive play space, where various sorting options compel users to search, analyze and compare by time, country, food, emotion, and number of tweets. Given the multivariate nature of the dataset, the various areas of the treemap were assigned visual marks: colour (to indicate range of emotion, red being most happy and blue being least happy) and size (to indicate quantity of tweets). Icons (stick men and money bags) were used to represent country obesity and GDP, respectively. These were adjusted for size to depict differing numerical quantities.

The visualisation directly takes on Shneiderman's Mantra, a design method especially useful when dealing with large data sets (Card, MacKinlay and Schneiderman 2009). This treemap design empowers users to first gain an overview and broad awareness, then move on to closer observation and analysis of the visual data by zooming and filtering, and finally, analyze the visual data with details-on-demand. In FoodMood this is accomplished with the ability to drill down to each individual tweet.

In the 'World View', the treemap consists of countries; here the size of the block represents the number of food tweets from a certain country. The colour of the block represents the average "happy sentiment" (the happiness percentage) of the collection of foods consumed in the specified country. There are various sorting and filtering options on the periphery of the treemap on the homepage. A 'simple/advanced' switch allows users to view the top 100 foods (if enough foods are available for the selected country) in a country versus all the foods tweeted. The other switch option allows to sort the treemap view by number of tweets, with largest to smallest blocks, as well as to sort by happiness percentage, so that the emotional representation is viewed from most happy to least happy.

Users can select a country from a list as well as sort options based on our other variables; e.g. 'most obese countries' and 'least GDP countries'. A timeline allows users to select either an interval or a point in time. This option can be used to search for specific days (or weeks) of interest.

Users can zoom into country blocks on the treemap to view the consumed foods from a selected country. In this step, the size of the blocks is the number of tweets about a certain foodstuff and the colour represents the sentiment rating. GDP and obesity levels for the selected country are available in the mouse-over alongside trivia.

FoodMood allows users to:

- Explore food tweets from 160 countries
- Discover the top 10 foods for all 160 countries represented
- Compare food tweets between countries
- Compare food sentiment between countries
- Compare countries with different GDPs as well as isolate the lowest and greatest GDP countries in one view
- Compare countries with different obesity levels and sort by most obese and least obese countries in one view
- Find the world's Happiest Foods (with the highest rating) and those foods with the most tweets
- Users can zoom in to view individual tweet(s) for every foodstuff
- Once the user is in this "tweet view" they can also compare this foodstuff across countries
- Perform a Google image search for foods

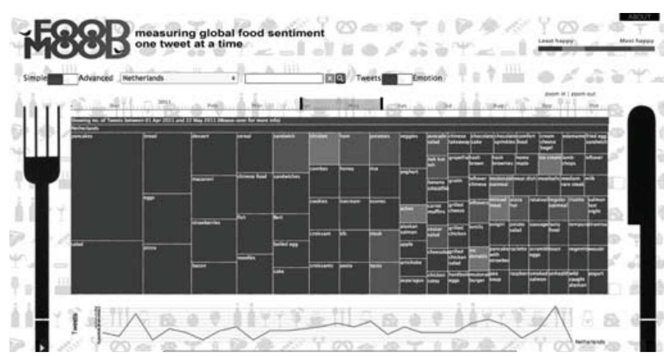

Figure 2. FoodMood Visualisation

Limitations

Like most data visualization projects, it is practically impossible to ensure complete objectivity in the process. As Enrico Bertini explains, 'even if the author tried to be neutral, the data itself can offer a partial view on the phenomenon' (2011). In the case of FoodMood data was cherry-picked to serve our purpose of investigating global food engagement and sentiment patterns as discussed by Twitter users. In the same regard we have also chosen to disregard certain other data.

The data pool consists of tweets by people who have access to the Internet and tweet in English. This restriction undoubtedly creates a large bias in the visualization, so it should be kept in mind that the snapshot of data will obviously not be completely representative of the entire world and especially so for the non-English-speaking countries.

Limiting our initial data set to only search for tweets containing the words 'for breakfast', 'for lunch', 'for dinner', 'I ate', and 'I'm eating' is inevitable considering the scope of this project. At this first iteration of the FoodMood application readers should keep in mind we have essentially invented a system to detect food items that has not been scientifically tested against other terms that could potentially be used. However, the current approach works successfully as the phrases chosen refer to eating as an individual action performed in near time. Though adding more phrases could actually worsen the performance of FoodMood it is something that forms a basis for experimentation in the future. When interpreting the findings of this application it is key to recognize that what the data tells us is as much a product of the data visualization tool, a hybrid of the raw data we find, and the specific ways we look for, categorize and process the data.

Findings

FoodMood reveals meaningful consumption patterns amongst Twitter users. It also provides meaningful data as a basis for further analysis. While it is true that Twitter does not necessarily represent the population of a country, and that FoodMood cannot collect data from all those on Twitter, it is also true that a person, to share something about food on Twitter, has to be engaged (emotionally affected to the point of action) to tweet. FoodMood in fact measures, implicitly, not only cultural ties of food to countries, but food engagement too. Changes in this engagement can be measured via the changes in the number of tweets per foodstuff in a country. As the Tweet dataset grows it will allow researchers the chance to answer questions about why some foods are more engaging than others. So too, other datasets can be applied to the visualization to reveal patterns concerning other topics such as health-care expenditure per country, sustainability, fair trade food or number of calories consumed. Presenting this key information about food consumption in a visually engaging way can help distil the essential changes that could then impact our food-purchasing choices and improve health.

Top 50 Tweeted Foods[3]

Echoing the findings of the WHO report on the global issue of rising obesity levels (2011), 58% of the 50 most tweeted about foods globally contribute to obesity, as represented in Fig.3. These include fast food brands tweeted by name (e.g McDonald's, Burger King, KFC, Taco Bell) and foods with a high glycemic index, fat and sugar content (e.g pie, brownies, chocolate, fried chicken).

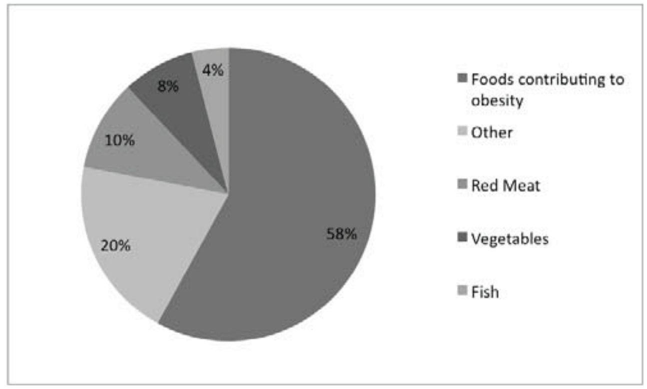

Figure 3. Foods with Most Tweets (Global)

Majority Positive Sentiment

Overwhelmingly the sentiment expressed by collected tweets by FoodMood is positive, with certain foods showing peaks at certain times of year, eg. chocolate over Easter. The sentiment scale on the visualization thus only reflects a rating from 'least happy' to 'most happy.' In line with previous research findings: pleasant emotions like satisfaction, enjoyment and desire were reported more often than negative ones in response to eating and tasting food (Desmet and Schifferstein 2008).

High Sentiment for Foods Contributing to Obesity

Both obese *and* countries with healthy Body Mass Index averages showed an overwhelmingly high sentiment for fast foods, high fat and high sugar foods. It is a significant implication that the most tweeted about foods in the world are mostly these foods that contribute to obesity. Beyond discovering trends like these, this data visualization can be used to cultivate self-awareness amongst users and/or advocacy groups to question why high food engagement in our society is predominantly with 'unhealthy' foods.

Global Popularity of Fast-Food Companies

The ubiquitous popularity of fast food stands out as a major trend in FoodMood. One or more of these four major

[3] Data sample: 1 May to 25 May 2011 and 1 January to March 14 2012.

multinationals are present in nearly all of the country views: McDonald's, KFC, Burger King and Chipotle. McDonald's is only absent when there are no outlets (ie. many African countries), indirectly revealing the global footprint of the fast food business. This not only represents the success of these brands amongst consumers but a powerful view on the vast globalisation and flattening of food culture. However, the popularity of fast food is context specific, as it does not receive the same sentiment rating across countries, e.g Dutch and British tweeters showed different sentiment towards Happy Meals and McDonald's Oatmeal.

High Sentiment Towards Meat

Meat in many parts countries in this visualization received an overwhelmingly high sentiment rating (70% and over). It was also widely tweeted about. This points to the vast global consumption of meat and that people, on average, enjoy it. The high sentiment and volume of tweets concerning meat confirm the state of current food consumption patterns. That people are widely and happily consuming meat has large implications for, amongst others, water resources. (For every one kilogram of beef produced 16,726 litres of water is required (Hoeksa 2003).)

Food Paradoxes

Instances of cultural specificity were revealed in FoodMood. In each of the country views nation-specific foodstuffs were represented on the treemap. A few examples include: Vegemite (a popular Australian spread); biltong (a cured meat specialty unique to South Africa); Biryani and chiapati (traditional Indian curry and side bread); bun cha (a Vietnamese grilled pork noodle soup) and Lechon (a traditional Argentinean dish of roasted suckling pig). However, there are some foods that enjoy near-ubiquitous popularity, such as pancakes, eggs and pizza. These are also foods that often appear on a country's top happiest food list. This may represent the flattening of global food culture or simply be a symptom of food globalization.

Gaps Between Rich and Poor

FoodMood shows a stark contrast when comparing African neighbours with differing Gross Domestic Product (GDP) like Zimbabwe and South Africa. Zimbabwe (low GDP) included tweets about curried goat while their neighbour (South Africa, higher GDP) contained tweets about lemon meringue pie. Nothing magnifies the difference between cultures as well as economic well-being quite like what people are eating.

Reflections of Immigration and Traces of the Past

The presence of certain ethnic foods in countries points to the influence of immigrant communities that reflect cultural diversity across the globe and patterns of globalisation. For example, in Argentina, foodstuffs such as Sisig and Nilaga are traditional Filipino dishes. Asian Latin Americans have a centuries-long history in the region, starting with Filipino immigrants in the 16th century. FoodMood often reflects a country's political history through food, revealing traces of former colonizers. For example, croissants, a popular French baked good, appeared in the country view of Vietnam, a former French colony.

As the resolution of the data grows *FoodMood* will be able to reveal, at finer levels of granularity, how food is being consumed at a city level. As geolocation data becomes more available so the analysis of food, obesity and sentiment can be used to understand transitions or norms that exist in cities.

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