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Abstract

This example thesis briefly shows the main features of our thesis style, and how to use it for your purposes.

Contents

Chapter 1

Introduction

Chapter 2

Data

In this section we describe the filtering process of the tweets and the creation of three lexicons. The food lexicon contains keywords with food related terms (e.g. *rice, wheat, milk*) where the predictor lexicon contains keywords with factors influencing the price and supply of the goods (e.g. *pricey*, *cheap*, *available*). The external factors lexicon similar to the former predictor lexicon tries to capture the price and supply of different food commodities (e.g. *oil, unemployment, flood*). They differ that the former looks explicitly at keywords directly associated with food terms which give an indication about the price fluctuation. The later is concerned with keywords describing external factors such as *oil*. We downloaded 2 TB of tweets from the internet archive [1] over a span of October 2011 - September 2014. The filtering process resulted with 1047698 food relevant tweets and 523549 tweets of influencing factors.

Firstly, we detail an algorithm Hyperspace Analogue to Language (HAL) [7] which was used to find relevant keywords for our lexicon. We then describe our framework for retrieving food related keywords that form our food lexicon. The subsection Feature Definition describes how we define different predictor categories, followed by an illustration of the procedure we applied to retrieve the predictor keywords. In the chapter Factors Keyword Selection we motivate the term selection of the external factors lexicon. Lastly, we describe the filtering algorithm used to create our dataset.

2.1 Hyperspace Analogue to Language

HAL creates a semantic space from word co-occurrences [7]. By using a sliding window parsing mechanism, the frequency of each term co-occurring within a fixed window size is recorded. It is important to note that HAL only records the terms before the word we wish to analyse the context from.

[1] https://archive.org/details/archiveteam-json-twitterstream

The terms after the word will appear in the column in the matrix that corresponds to that word. The matrix is created by storing a vector for each word with the number of co-occurrences of every other word in the corpus. Hence, if our corpus contains N different words the resulting HAL space would be an $N \times N$ square matrix of co-occurrences. Every time a specific word appears within the fixed window size the co-occurrence vectors are updated. For each co-occurrence HAL applies a scoring function. Words that appear closer, receive an inversely proportional score to its distance.

To illustrate the idea [4] gives an example of a simple sentence *"The horse raced past the barn fell."* in Table 2.1 with a sliding window of five. Let's consider the first row. *"The"* precedes *"Barn"* twice. Once within a distance of five and the other time it directly precedes the word *"Barn"*. Hence, that cell receives a score of five for the proximate one and a score of one for the word further away resulting in a final score of six.

Following the creation of the matrix we concatenate both the column and row vector of a word, where the former represents the preceding words and the later the following. To compare the distance of the vectors we used the cosine similarity function.

	Barn	Horse	Past	Raced	The
Barn		2	4	3	6
Fell	5	1	3	2	4
Horse					5
Past		4		5	3
Raced		5			4
The		3	5	4	2

Table 2.1: Toy example of HAL

2.2 Food Keyword Selection

The filtering of the dataset was initially performed with a simple list of food related keywords. To avoid ambiguities we will refer to the initial keyword list as K_i. As a first source for our set K_i we used the most common traded food commodities as it would easily allow us to verify our results using the price dataset made available by IMF [2]. We further decided to include the ten most important staple foods that feed the world as defined by Allianz[3]. Tweets were retrieved through exact term matching, i.e. a tweet containing the term *foods* would not match on the keyword *food* where the reverse is also

[2] http://www.imf.org/external/np/res/commod/index.aspx

[3] http://knowledge.allianz.com/demography/health/?767/the-worlds-staple-foods

true. We mimic the term matching twitter performs. In the initial round we optimised for coverage and hence avoided further filtering steps. The result was a collection of 1047698 tweets posted by 949085 user.

Looking at the distribution of the food related tweets we realised that we would have to categorise our lexicon in order to have sufficient data for further analysis. Where global keywords such as *food* are highly represented, more specific keywords such as *beef* occur infrequently. Other than the sparsity of the data we also have the problem of ambiguous keywords. *Soy* is such a keyword that refers in English to the *bean* and in Spanish to the verb *to be*. To avoid such ambiguity we extended the term to make it distinct (e.g. *Soy* → *Soy Bean*).

To create categories we chose to mimic the categorisation of the FAO [4]. FAO tries to measure the overall food fluctuation by five different food categories namely *meat, dairy products, cereals, vegetable oil* and *sugar*. The weighted average of those five categories as illustrated in [5] defines the international food price index. We additionally created a further category named *Other Food of Interest*. This category contains general keywords (e.g. *food, dinner or lunch*) and food keywords that cannot be assigned to one of the five categories, but frequently occur (e.g. *coffee, tea*). To be considered frequently the set of tweets containing the keyword needs to be $> 1\%$ of the total sample.

The six subsets s are $\in K_e$ where s is one of the six categories mentioned above. C is an imaginary set that contains the five categories *meat, dairy products, cereals, vegetable oil, sugar* each being a subset containing all possible food items belonging to a specific category (e.g. the subset dairy would contain all possible dairy products). If the following relationship holds $k \in C$, where k is a keyword, for any keyword $k \in K_i$, we consider $k \in K_e$. For all keyword $k \notin C$ the condition of it being frequent is evaluated and if true added to K_e. Food commodities that could not be assigned to any of the six categories were discarded (e.g. *orange, cocoa, onion*). Upon manual examination of the dataset we realised that people are much more likely to talk about a specific food product rather than the raw material. *Cereals* are not a public interest. However products such as *bread* or *flower* occur much more frequently. The set K_e was further enriched by using food products that have been identified by [1] in set K_f only $\forall\ k \in K_f$ that are also $\in C$. To further improve our coverage of the six food categories we filtered for synonyms and contextual similar words using HAL.

2.2.1 Our Approach

We took several steps in order to improve our detection of the desired food commodities. K_e was created as follows:

[4] http://www.fao.org/worldfoodsituation/foodpricesindex/en/

1.) We add all keywords $k \in K_i$ to K_e only if $k \in C$ or k is frequent

2.) Further we add all keywords $k \in K_f$ to K_e only if $k \in C$

3.) We create a HAL space using a random subsample of 10% from our initial collection with all keywords that occur > 100. $\forall c \in C$ we pick the keyword $k \in K_e$ that most frequently occurs over the entire sample and retrieve the top 500 similar terms. We hand select those that are $\in C$.

The keyword set K_e was used to perform exact term matching on the tweets collected from the internet archive. The resulting set of keywords in K_e forms our Food Lexicon.

Lexicon / Subset s	Keywords (i: from initial set, e: from K_f , h: from HAL space)
K_i Food	meal (i), meals (i) ,food (i), foods (i), wheat (i), rice v, maize (i), carley (i), soybean (i), soy (i), meat (i) , beef (i), cattle (i), chicken (i), poultry (i), lamb (i), swine (i), pork (i), fish (i), seafood (i), shrimp (i), salmon (i), sugar (i), bananas (i), oranges (i), coffee (i), cocoa (i), tea (i), milk (i), yams (i), cassava (i), potatoes (i), sorghum (i), plantain (i), nuts (i), onion (i), salt (i), egg (i), dairy (i), cereals (i)
K_e Meat	meat (i), lamb (i), pork (i), swine (i), chicken (i), poultry (i), beef (i), sausage (e), rib (e), pastrami (e), kidney (e), liver (e), ham (e), bacon (e), chorizo (e), salami (e), sheep (e), boeuf (e), oxen (e), kine (e), steak (e), cow (e), brisket (e), veal (e), tenderloin (e), sirloin (e), poulet (e), volaille (e), hot dog (h), hamburgers (h), meatballs (h), burgers (h), goat (h), cattle v, turkey (h), pig (h)
K_e Cereals	wheat (i), atta (i), starch (i), farina (i), bran (i), ethanol (i), biofuel (i), rice (i), corn (i), maize (i), ravioli (e), barley (e), scotch (e), whisky (h), oat (h), bread (h), flour (h), gluten (h), pasta (h), noodles (h), beer (h)
K_e Oil	coconut oil (i), corn oil (i), olive oil (i), palm oil (i),peanut oil (i), sunflower oil (i), rapeseed oil (i), safflower oil (i),soybean oi (i), sunflower oil (i), soybeans (i), soya (i), soy sauce (i), soja (i)
K_e Sugar	sugar (i), sugarcane (i), syrup (e), energy drink (e), cola (e), chocolate (e), nestle (e), cookies (h), cupcakes (h)
K_e Dairy	dairy (i), egg (i), milk (i), kefir (e) , butter (e), yogurt (e), quark (e), mozzarella (e), cheddar (e), parmesan (e), buttermilk (e), ricotta (e), feta (e), romano (e), provolone (e), colby (e), edam (e), eggnog (e), pimento (e), cheshire (e), roquefort (e), icecream (h), milkshake (h), cheese (h), cream (h)
K_e Other	meal (i), meals (i), food (i), foods (i), fish (i) , prawn (i), seafood (i), salmon (i), tea (i), coffee (i), dinner (h), lunch (h), breakfast (h), dish (h), cuisine (h)

Table 2.2: A Summary of the Evolution of our Food Lexicon

2.3 Predictor Keyword Selection

From our basic food lexicon we proceeded to extract features that we could use to predict the price and the global food security index. The FAO measures food security based on four dimensions namely *Access, Availability, Stability* and *Utilisation*. Where *Access* mostly captures the supply of food, *Availability* is concerned with the affordability of the basic goods. *Utilisation* captures the nutritional value of the food and lastly *Stability* is a measure of the other three dimensions over time. For food security objectives to be realised, all four dimensions must be fulfilled simultaneously [9].

To model food security we focus our work on those four dimension namely *Access, Availability, Utilisation* and *Stability*. Together those predictor categories build the set C_p. Attempts have been made to capture Availability by the UN [6].

We define the predictor category *Access* by looking for tweets containing price as a keyword as in [6] but improve the recall by including synonyms of *price* that appear in the same context. *Availability* was defined in similar fashion by matching keywords that appear in the context of food availability as in [2], however a different set of keywords was selected as described in the following chapters. Unlike [1] we don't measure food Utilisation by observing the exact diet but capture the people's food needs. Lastly as a measure of *Stability* we focused our attention on economic stability. Keywords in the context of poverty were selected to match this predictor category similar to [10] [2].

2.3.1 Motivating a Semantic Approach

In this section we try to comprehend which words are associated with the above-mentioned categories in C_p. More specifically what words are represented in the context of *food supply, food price, food needs* and *food poverty*. To achieve this we need a methodology for representing the meaning of a word. The reason that we analyse the context of a word is to identify new words that have a similar meaning or given the same context express the same thing. The later is concerned with identifying synonyms where as the former looks at contextual similarity. For example, let's look at the word *mold* and *available*. Those two words seem unrelate, but given the context of food they express the same thing. Namely an abundance of food. Through the role of the context they posses elements of items similarity but by themselves they would never be considered words with similar meaning. It's important to stress that they are not similar because they occur frequently locally, but because they occur frequently in similar sentential context. Burgess et al. [4] argues that a simple local co-occurrence analysis misses to capture a lot of relationships. For example the word street and road are basically synonyms however the seldom locally co-occur. They do, however occur in the same context. This observation motivated us to deviate from the commonly used co-occurrence analysis an take a step further to improve the precision of our filtering framework.

2.3.2 Our Approach

We use a large text corpus of around 23860931 words. As a source we used a random sample of 10 % from our food related tweets. Our corpus of food related tweets has a number of appealing properties as it covers a large vocabulary centered around food. Unlike most corpora that represent formal business reports or specialised dictionaries our food corpus represents everyday speech. This gives us a closer approximation on how people would talk in the context of our predictor categories.

The vocabulary of the HAL model contains 14084 words. The initial set of words in our corpus was filtered only to contain those words that appear at least 100 times. Words occurring infrequent were discarded as well as stop words and punctuations. We will refer to this set of words as F_c. Using the words $w \in F_c$ we produced a 14084 by 14084 matrix with the co-occurrences within a window size of five. Since vector similarity measures are sensitive to the magnitude of the vectors we normalised all the vectors to a constant length. Once the HAL space was created we performed the following steps to retrieve the desired keywords for our four categories.

1.) $\forall k \in K_e$ choose the keyword k with the highest occurrence form the entire sample. Let's call it k_{max}

2.) $\forall w \in F_c$ perform a similarity measure with k_{max}

3.) Retrieve the 500 most similar words and hand-select one word for each element of C_p (e.g. since we have four categories the result should be four words)

4.) For each of those hand-selected words apply HAL and compare it $\forall$ $w \in F_c$

5.) For each predictor category retrieve the 500 most similar words and manually select relevant keywords. Elements were selected that could be clearly related to the given topic (e.g. *available* and *production* for supply). Ambiguous ones were also included if they had a clear relationship to food related terms (e.g *rise, increase*).

The high-level intuition of this procedure is as follows. The first step will give us the most prominent food term. This is most likely going to be something general such as the keyword *"Food"*. Step 2 and 3 will allow us to identify the most contextual similar keywords for each category. So the keyword is retrieved that is most likely used to describe supply in the context of food. In step 4 and 5 we aim to retrieve similar words that could describe supply but maybe appear more frequently in different contexts. In other words, we aim to find synonyms here.

2.3.3 Results

Other than the words for our categories of interest HAL highlights some clear topics associated around food. As expected other contextual similar words were other food items building the clear majority of the retrieved words. Interestingly there was also a high percentage of country names in the retrieved results. Looking more closely at the retrieved countries we could see that most of them have a clear association to food. Where the majority of the retrieved countries such as Thailand, Bali [5] or the cities Singapore and Paris [6] are considered to be famous holiday destinations for food lovers other retrieved countries such as Pakistan, Syria, Jakarta India or the Philippines [7] are cities with a clear history of food insecurity and political unrest.

Words that fell into our categories of interests were words such as available, profit, price, sustainability, progress, sales, war, easy. The four words we used to model the predictor categories were *available* for supply, *price* for price, *children* for poverty and *help* for needs. Where the first two terms are self explanatory the term children was selected because in [8] anthropological studies have shown that children are seen as a symbol of poverty and social exclusion . For the category needs keywords such as *yum* or *foodporn* had a high similarity with the term *food* but those terms are nearly exclusively used to express a positive sentiment. Words that also showed high similarity such as *abuse* and *protest* only retrieved a small amount of relevant keywords. We hence explored the results of the other categories and found *help* which was retrieved from the results of *price*. It was deemed as a good indicator as it can express both a positive and negative sentiment associated with *needs*.

[5] http://www.nomad4ever.com/2008/08/24/top-10-popular-foods-of-asia-explained/

[6] http://www.hellotravel.com/stories/best-food-cities-in-world

[7] http://foodsecurityindex.eiu.com/Country

Lexicon / Subset *s*	Keywords (i: from initial set, e: from K_f , h: from HAL space)
Food Supply	*available*, giveaway, coupons, told, growth, sustainability, nomnom, receive, indonessia, berlin, program, institute, survey, news, farming, journal, strategy, price, india, check, canada, production, campaign, protection, imports, launched, rating, storage, nutrition, restaurant, resources, trends, container, stall, government, distribution, processing, impact, policy, consumption, stores, exports, opportunities, harvest,price,savings,discount, budget, profits, increase, rise,relief
Food Price	*price*, issue, india, coupon, health, children, news, malaysia, discount, benefit, syria, asia, indonessia, philippines, grothw, dubai, consumer, campaign, sold, agriculture, available , sustainability, thailand, farming, markets, harvest, program, success, foundation, crops, politics, demand, purchase disaster, rates, safe, cost, association, nutrition, nation, sponsored, fundraiser, protest, deal, giveaway, growing, dangerous, threat future, programs, fighting, farms, consumers, support, jakarta, pakistan, africa, curtesy, poverty, exports drought, funding, bill, summit, delhi, rating, priced, justice, avoid
Food Poverty	*children*, community, source, future, issue, safe, project, growing, support, benefit, india, health, asia, baby, government, dangerous, area, agriculture, politics, poverty, cultures, obesity, tax, changes, program, freedom, price, impact, news, report, nutrition, help, country, syria, sustainability, philippines, success, awesome, farm, donate, diet, foundation, indonesia, summit, supplies, israel, farms, farming, kills, cash, crops, confernece, projects, seeking, nation, fight, protection, courtesy
Food Needs	*help*,power, amazing, thanks, future, children, beyond, yummy, issue, death, killing, helping, brilliant, delicious, awesome, tasty, freedom, kill, needed, nice, healthier, benefits helps, feeding, love, tax often, health, incredible, politics, destroy, expensive, increase, yum, heavenly, trash, necessary, cheap, enjoy, smiling, struggle, disaster, stress

Table 2.3: Keywords of Predictor Categories

2.4 Factor Keyword Selection

2.5 Filtering

Following the creation of the four categories we will use polarities to model the price variation. For example, the category *price* has two polarities: *high* and *low*. In [2] we worked on a filtering mechanism to extract relevant tweets and to assign them to the relevant polarities. In order to achieve this goal, a prediction lexicon with a total of four categories was built (*price, poverty, needs, supply*). We will refer to it as *D*.

For every word in a tweet and for every word in D the stem is computed. This is necessary to capture tweets that may contain a predictor term that is not in its base form. Fore example a tweet containing the word *pricey* would not match the term *price*. Furthermore the framework also accounts for misspelt words. To do this in a computationally efficient way the algorithm computes the edit distance between a given word and terms from the predictor set D. If the error is within a fixed threshold the predictor term with the minimal edit distance is returned.

Experiments showed that sentiment analysers such as SentiStrength [12] or Stanford CoreNLP [11] performed poorly on microblog content. Hence, the decision was made to extract the sentiment by having specific terms for each sentiment (polarity). In addition one had to account for changes in polarity through negations such as *never* and *not* which inverted the polarity of a predictor category term.

We however choose to deviate from this approach and use a sentiment analyser despite the bad results. There were two reasons for doing so. 1.) Hutto et. al recently published a new sentiment analyser VADER [**?**] with an F1 Classification Accuracy = 0.96 which outperformed human evaluators. 2.) Often keywords can not be manually assigned to a polarity without knowing it's context. Besides the above mentioned benefits VADER allows us to obtain a degree of sentiment by analysing grammatical and syntactical conventions that humans use when expressing sentiment intensity. For example it accounts for emoticons which are commonly used to express a sentiment or even acronyms such as *LOL, WTF*. It's further worth mentioning that VADER is an unsupervised approach and is well suited for streaming data.

2.5.1 Evaluation

2.6 Discussion

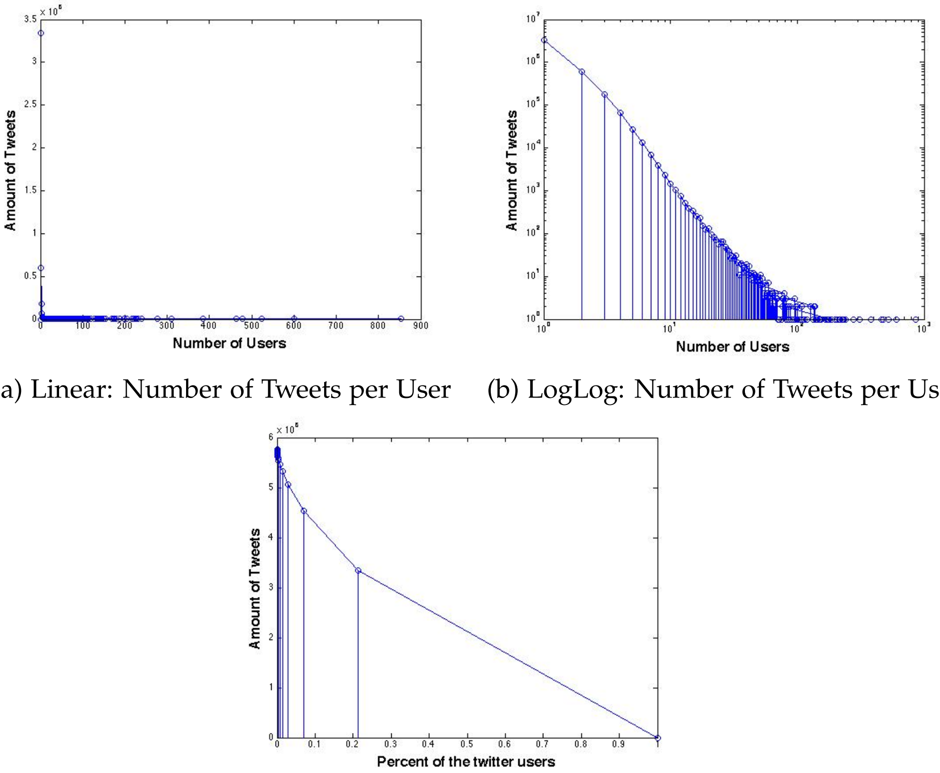
Chapter 3

Analysis

3.1 General Stats

Twitter is a social network and in general such networks follow a power law distribution [13]. We see in the bellow Figure **3.1a** and Figure **3.1b** that the distribution of the number of tweets per user slightly deviates from a normal power law. A lot of individuals have sent only a few tweets about the subject and only a small number of users have sent a large amount of tweets. Unlike [3] suggest the contribution participation level of 80 %, 20 % does not seem to apply to tweets about food. In Figure 3.1c we can see that the curve is very flat. About 40 % of the tweets are caused by 20 % of the users. This deviates highly form the normally observed 80 %, 20 % ratio. We assume that this is due to the wide spread interest of the topic.

Our framework for the data acquisition successfully increased the total volume of food related tweets. From an initial 2.6 M tweets we raised the entire volume by 110% to a total of 5.6 M food related tweets. The distribution of the volume per food term is displayed in Figure 3.2a. We illustrate in orange the added volume alongside the initial size in blue. The most popular food terms on twitter are general terms such as food, dinner and lunch. Within the 10 most popular terms we found that three beverages (coffee, beer, tea) were represented. The most popular traded commodity term on social media is chicken. We further show the distribution of the categories in 3.2b. By far the highest contribution has the category *others* due to general food related keywords such as *dinner* or *food*. It builds the absolute majority with 51 %. Meat related keywords has the second highest contribution with around 15 % followed by 12% sugar, 11% cereals, 10 % dairy and lastly 0.2 % Vegetable Oils. Interestingly the volume roughly follows the economic importance of the different categories with the only outlier being sugar [9]. We assume this is due to the highly popular products *coca cola* and empty chocolate which caused alone 70 % of the sugar related tweets.

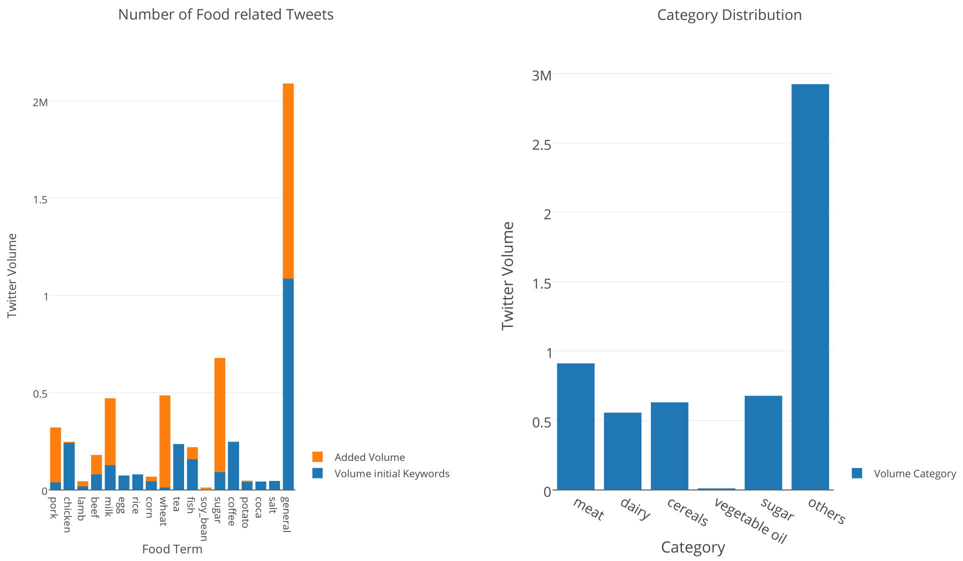


(a) Linear: Number of Tweets per User

(b) LogLog: Number of Tweets per User

(c) Distribution: Number of Tweets per User

Figure 3.1: Volume of Tweets per Keyword and per Category



(a) Overall Distribution

(b) Category Distribution

Figure 3.2: Volume of Tweets per Keyword and per Category

Appendix A

Dummy Appendix

You can defer lengthy calculations that would otherwise only interrupt the flow of your thesis to an appendix.

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