HOMOPHILIC SELF ORGANIZING FEATURE MAPS: FINDING TOPICS ON SOCIALY CONNECTED DATA, USING SOCIAL NETWORK RELATIONS

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Dissertação para obtenção do Grau de Mestre em

Engenharia de Redes de Comunicações

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Outubro de 2014

Acknowledgments

Remember that your parents have paid for the last 20 something years of your studies and that your advisor had to read this document.

Abstract

Clustering is a widely used technique in data analysis. In this thesis, a generically lgorithm used for clustering is modified in order to enhance the value of socially connected ententies.

To achieve this, we present RubySOM. A framework for easy construction of custom Self-Organizing Maps. With it, it is possible to dinammically change multiple parts of the algorithm, making it extremlly flexible solution to create, train and run custom implementations of the algorithm.

With RubySOM, a relational aware version of the SOM algorithm was created in order to better identify topics on the social network twitter.

Keywords

topic detection, twitter, self-organizing maps, classification, clustering

Resumo

Palavras Chave

detecção de tópicos, twitter, mapas auto organizados, classificação, agrupamento

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List of Acronyms

SOM Self-Organizing Maps

NLP Natural Language Processing

U-Matrix Unified Distance Matrix

TF-IDF Term Frequency–Inverse Document Frequency

BMU Best Matching Unit

LDA Latent Dirichlet Allocation

TDT Topic Detection and Tracking

VSM Vector Space Model

IR Information Retrieval

ML Machine Learning

ANN Artificial Neural Network

MDS Multi Dimensional Scalling

PCA Principle Component Analysis

URL Uniform Resource Locator

JSON JavaScript Object Notation

CSV Comma Separated Values

1

Introduction

Contents

With the evolution of social network websites like Facebook and Twitter, the amount of pertinent content about a specif issue is increasing dramatically, which calls for new ways to make catalog this sense of and data. The usage of social networks for branding quality and on-line marketing is specially compelling since 19% of all tweets [13] and 32% of blog posts [26] are about brands or products. Nevertheless, finding topic sensitive information on social networks is extremely complicated due to the fact that documents have very little content, slang vocabulary ,orthographic mistakes and abbreviations. Asur, Sitaram and Huberman [2] successfully predicted box-office revenues by monitoring the rate of creation of new topics based on debuting movies. Their work outperformed some traditional market-based predictors.

Thus academic and enterprise worlds started looking at Machine Learning for new ways to achieve revenue or simply explore and discover patterns in data. As a consequence, the Machine Learning course at Standford is the one with more students enrolling in the year of 2014 [1] with more than 760 students enrolled.

Using unsupervised Machine Learning (ML) Le et al. [20] was able to achieved 81.7% accuracy in detecting human faces, 76.7% accuracy when identifying human body parts and 74.8% accuracy when identifying cats. He used a 9-layered locally connected sparse auto-encoder with pooling and local contrast normalization on a large dataset of images (the model has 1 billion connections, the dataset has 10 million 200x200 pixel images downloaded from the Internet). This dataset was trained using model parallelism and asynchronous SGD on a cluster with 1,000 machines (16,000 cores) during three days. Even though the amount of computing power used in this project was of several order of magnitude, it is remarkable how an unsupervised algorithm could achieve such results.

Even though a lot of solutions have arisen in order to automate real time searches, topic categorization and many other data intensive tasks are still done manually. Twitter still uses humans to deliver ads to trending queries, states Edwin Chen's Data Scientist responsible for ads quality at Twitter. On his blog post [2], Edwin Chen describes the process of delivering real time adds to trending queries at Twitter. The main problems that arise in the Twitter platform in order to identify rising topics are:

- The queries people perform have never before been seen, so it is impossible to know beforehand what they mean.
- Since the spikes in search queries are short-lived, there's only a short window of opportunity to learn what they mean.

This means that when an event happens, people immediately come to Twitter in order to know what is happening in a determined place. Twitter solves this issue by monitoring which queries

[1] http://www.forbes.com/sites/anthonykosner/2013/12/29/why-is-machine-learning-cs-229-the-most-popular-course-at-stanford/

[2] http://blog.echen.me/2013/01/08/improving-twitter-search-with-real-time-human-computation/

are currently popular in real time, using a Storm topology [3]. After the queries are identified, they are sent to a Thrift API [4] that dispatches the query to Amazon's Mechanical Turk service [5] where real people will be asked a variety of questions about the query.

Social Media Analytics is another raising topic that draws from Social Network Analysis [16], ML, Data Mining [33], Information Retrieval (IR) [29], and Natural Language Processing (NLP). As stated Melville et al. [26], 32% of the 200 million active bloggers, write about opinions on products and brands, while 71% of 625 million Internet users read blogs and 78% of respondents put their trust in the opinion of other consumers. In comparison, traditional advertising is only trusted by 57% of consumers. This kind of data drives companies to Social Media Analytics as a way to know what people are saying on the web about their companies and products. This new worry has brought to life a lot of new startups like Sumal[6] or ThoughtBuzz[7], but also solutions from the old players like IBM[8] and SAS[9]

Its also important to notice that in the last few years Data Science/Analysis has been a trending topic, mostly due to the fact that big dot-com companies have been having high revenues by exploiting user specific information in order to deliver ads and sell products. Not surprisingly that if you look that in the top ten ebooks sold by O'Reilly throughout 2013, four are about data science [10].

1.1 Motivation

Clustering analysis has been widely used throughout the times, from its first occurrence in England, where John Snow was able to map a wider amount of people infected with cholera to a well in the center of London. Nowadays the applications are endless, and fields where it is applied are quite vast.

Specifically with a greater amount of people describing events around them, and their lives on social media, it is increasingly more challenging to categorize this data, due to its sparsity and volume.

However, data generated on social networks, have more information than simply written text, on a tweet, or a photo published on Facebook. Data generated in social network is connected by entities, and these entities tend to be closer to other entities with the same kind of interests [25]. In this thesis we will explore how a clustering algorithm can be altered in order to add social relevance to its fed data. By focusing on using an unsupervised learning technique based on

[3] http://storm-project.net/
[4] http://thrift.apache.org/
[5] https://www.mturk.com/mturk/
[6] https://sumall.com/
[7] http://www.thoughtbuzz.net/
[8] http://www-01.ibm.com/software/analytics/solutions/customer-analytics/social-media-analytics/
[9] http://www.sas.com/software/customer-intelligence/social-media-analytics.html
[10] http://shop.oreilly.com/category/deals/bestoforeillydotd.do?code=DEAL&cmp=twnabooksvideosinfo-authornote_best_of_2013

neural networks named Self-Organizing Maps (SOM) [18] in order to detect topics in Twitter posts, by using the Social Network users as base neurons for clustering. After the network is trained, it will be possible to categorize tweets in real time.

1.2 Objectives

The main objective of this project is to find topics on tweets by contextualizing the social network involving the person that authored the tweet in the clustering process.

We start by building a dataset, in order to train the SOM, that will later classify each future tweet that arrives on the network without further delay.

After creating the dataset, we will try to find clusters of topics using the default SOM approach, converting each tweet to Vector Space Model (VSM). After analyzing the results from the default SOM approach, the algorithm will be changed in order to give relevance to the fact that there is a relationship between authors of tweets.

1.3 Contributions

The main contributions of this work are as follow:

- A method to enhance topic discovery on data with small text corpus and high social significance.
- A framework to easily edit multiple parts of a SOM algorithm, by passing high order functions as configuration.
- To develop highly customizable infinite tweeter crawler that preserves the social network.

1.4 Dissertation outline

Explain how did you organized your thesis.

2

Background

Contents

In this section, we will start by generally describing what clustering is and how it works. We will then outline how SOM [18] perform, which is the document clustering algorithm used on this thesis.

2.1 Document Clustering

Document clustering is an optimal division of documents into categories without prior knowledge of the data that is being organized, based only on the similarity between them. Due to the fact that no prior knowledge of the data has to be known, document clustering is labeled as Unsupervised ML [10].

Liu et al. [22] asserted that document clustering can be used in a variety of Computer Science fields, such as:

- Natural Language Preprocessing.
- Automatic Summarization.
- User preference mining.
- Improving text classification results.

There are two main types of document clustering: hard clustering and soft clustering. In hard clustering, one document can only belong to one cluster, while in soft clustering one document can belong to multiple clusters.

The clustering process usually works as described in Figure 2.1. In the first step, a data set must be provided with the documents to be clustered. The second step is where non relevant words are removed from the documents, to improve clustering quality [14].

The third step is characterized by converting the keywords of each document into vectors. The most common model used for this task is VSM. In VSM, each vector dimension represents one detected keyword and each document is represented by the vector of keywords in the feature space. This process is illustrated in Figure 2.2 and works in the following way:

- **First step:** string tokenization, and token selection. In this case, stop words and repeated words will be removed.
- **Second step:** string to VSM conversion. Each different word will correspond to a position in the array, and its value will correspond to the number of occurrences.

There are many clustering algorithms. In the following section we will describe the particullar case of the SOM algorithm, the solution used in our work.

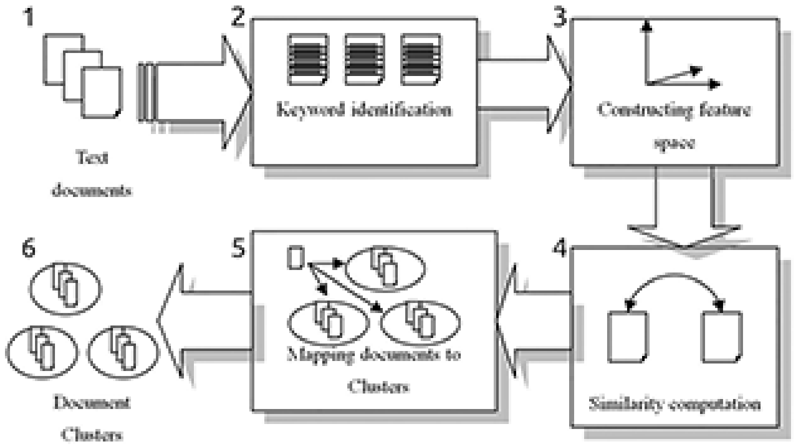


Figure 2.1: Text clustering main framework [9]

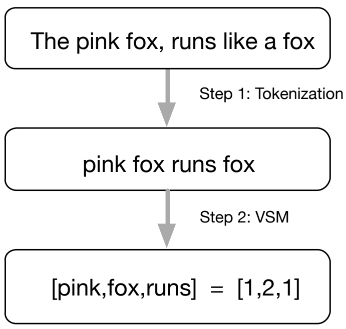


Figure 2.2: Text tokenization and transformation to Vector Space Model.

2.2 The Self-Organizing Map

SOM are a two layer recurrent Artificial Neural Network (ANN) that has the desired property of topology preservation, thus mimicking the way the cortex of highly developed animals brains work. SOM allow cluster visualization of multi-dimensional data, similar to methods such as Multi Dimensional Scalling (MDS) [19] and Principle Component Analysis (PCA) [12] .

Bação et al. [3] described the basic idea behind SOM as a mapping between input data patterns into a n-dimensional grid of neurons, or units. That grid is also know as the output space, as opposed to the initial space — input space — where the input patterns reside. An illustration of both spaces can be seen in Figure 2.4.

SOMs work in a similar way as is thought the human brain works. Analogously to the human brain, SOMs also have a set of neurons that, through learning experience, specialize in the identification of certain types of patterns. These neurons are responsible for categorizing the input patterns for which they are responsible to identify. Nearby neurons will be organized by similarity, which will cause similar patterns to activate similar areas of the SOM. With this topology preserving mapping, the SOM organizes information spatially, where similar concepts are mapped to adjacent areas. The topology is preserved in a sense that, as far as possible, neighborhoods are preserved throughout the mapping process. Output neurons are displayed in an N dimensional grid, generally rectangular, but other structures are possible, such as hexagonal or octagonal. The grid of neurons, in the output space, can be divided in neighborhoods — where neurons responsible for the same kind of input reside. In SOM, neurons will have the same amount of coefficients as the input patterns and can be represented as vectors.

Before describing the algorithm, it is important to define two key aspects of the SOM: the learning rate and the quantization error. The learning rate is a function that will be decreased to converge to zero. It will be applied to winning neurons and their neighbors in order for them to move toward the corresponding input pattern in progressively smaller steps. Quantization error is the distance between a given input pattern and the associated winning neuron. It describes how well neurons represent the input pattern. The radius of the neighborhood around the winning neuron is also particularly relevant to the topology of the SOM, deeply affecting the unfolding of the output space as stated by Bação et al. [3].

The learning phase is characterized by the Algorithm 1, which works the following way:

- **On line 1:** neuron closer to the input pattern is selected. The euclidian distance (Eq. 2.1) is generally used.

$$Dist = \sqrt{\sum_{i=0}^{i=n} (V_i - W_i)^2} \tag{2.1}$$

- On line 2 the winning neuron (p) previously selected on line 1 is updated, in order to better represent the inputt pattern. This process is represented on Figure 2.3. Also, all other

Algorithm 1: Self-Organizing Map [18]

Data: Input patterns $X = \{\overrightarrow{x_1}, \ldots, \overrightarrow{x_N}\}$, number of iterations t_{max}, neighborhood function $\sigma(t)$, learning rate $\epsilon(t)$

Result: Trainned map and clustered input patterns

Randomly initialize neurons, $w_i \in \mathbb{R}^D, \forall i$

for $t = 1 \; to \; t_{max}$ **do**

Randomly draw an input pattern, $\overrightarrow{x_d}$

1 $p = \arg min_i \{\|\overrightarrow{x_d} - \overrightarrow{w_i}\|\}$

2 $\overrightarrow{w_i} = \overrightarrow{w_i} + \epsilon(t) \cdot h_{ip}(t) \cdot (\overrightarrow{x_d} - \overrightarrow{w_i}), \forall i$

3 $\sigma(t) = \sigma_0(\sigma_f/\sigma_0)^{t/t_{max}}$

4 $\epsilon(t) = \epsilon_0(\epsilon_f/\epsilon_0)^{t/t_{max}}$

5 $t \leftarrow t + 1$

neurons inside a specific radius will also be updated, this process is described in Figure 2.4. Each neuron is updated with a different rate of influence determined by how far away it is from the winning neuron, which is defined by the neighborhood influence function $h_ip(t)$ the Gaussian (Eq. 2.2) is often used.

$$h_{ip}(t) = \exp - \frac{|\overrightarrow{a_i} - \overrightarrow{a_p}|^2}{\sigma^2(t)} \tag{2.2}$$

- **On line 3:** the size of the radius will be updated.
- **On line 4:** the learning rate is updated.
- **On line 5:** the number of iterations is incremented.

In order for the algorithm to converge, the learning rate and the radius of the neighbourhood need to decrease at a given rate. Generally exponential decay is used.

Algorithm 2: U-Matrix

Data: Input patterns $X = \{\overrightarrow{x_1}, \ldots, \overrightarrow{x_N}\}$, Trainned neurons $W = \{\overrightarrow{w_1}, \ldots, \overrightarrow{w_N}\}$

Result: U-Matrix

for $w_d = \overrightarrow{w_1}$ to $\overrightarrow{w_N}$ **do**

(NOTA: Nao sei muito bem como escrever isto numa formula matematica..) the average of all the distances between a neuron and all of the input patterns he represents

The prediction phase can start after the model is learned. On the prediction phase new input patterns can be quickly assigned to the SOM, without need to apply the learning rate to the winning neuron and his neighbors. Due to the fact that the input pattern will be assigned to the cluster that has nearest neuron is mapping. Thus it very easy and fast to classify new data now. As stated by Liu et al. [22] the advantages of using SOM is data noise immunity, easy to visualize data, and parallel processing.

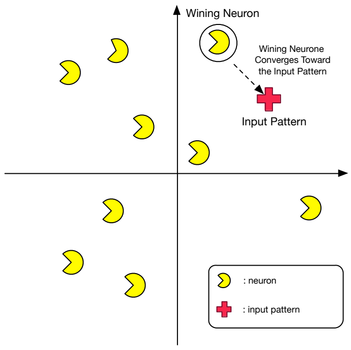


Figure 2.3: Winning neuron converging at learning rate

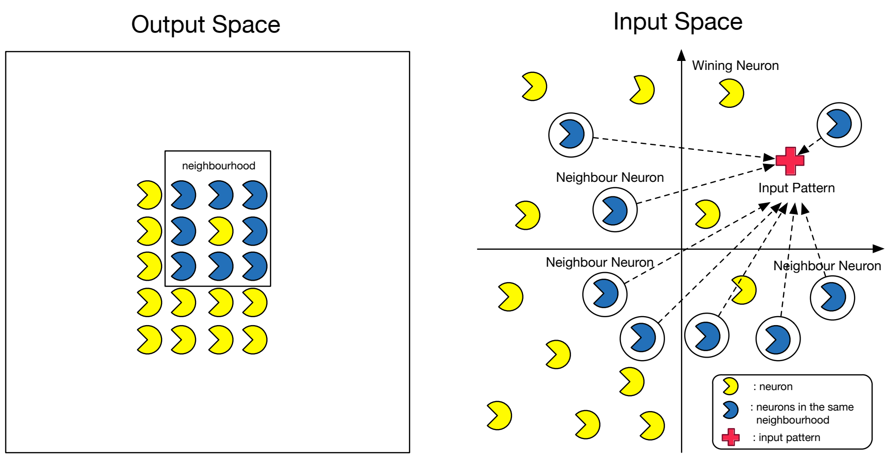
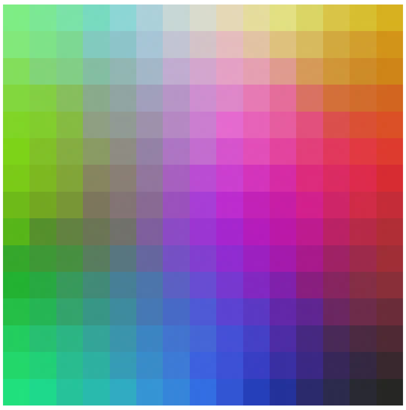


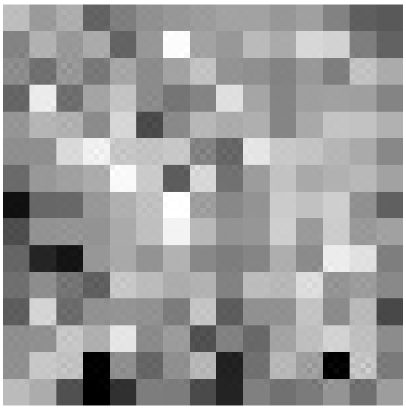
Figure 2.4: On the left the output space neighborhood, on the right the neighbors of the winning neuron converging in the direction of the input pattern

In order to visually interpret the result of the SOM, Unified Distance Matrix (U-Matrix) method may be used [3]. The U-Matrix is a representation of the SOM, in which, the average topological error between a neuron and all the input patterns he represents is displayed in a colour scale proportional to the maximum and minumum values obtained in the SOM.

Computing a U-Matrix is done by the Algorithm 2. Essentially, each neuron is responsible for representing a cluster of input patterns. The better a neuron represents an input patter and the smaller the distance between them both. Therefor, the better a neuron represents a group of input patterns, the smaller the average distance between himself and all the input patterns it represents. For representation purposes, after all the averages are computed a lighter color is assigned to the lower average, and the darkest color to the highest, and all the values in between must have a color proportional to its own value in reference to the edge values. An example of an U-Matrix can be seen in Figure 2.5(b)



(a) SOM ouputspace trained with random RGB vectors



(b) U-Matrix representing how well each neuron maps to input patterns it represents

Figure 2.5: U-Matrix and SOM output space, computed by training the SOM during 400 epochs, with 1500 random input patterns representing an RGB color.

3

State of the art

Contents

This section provides insight of work done in several research areas that are related to the project. In section 3.1 work done using Self-Organizing maps will be described. Section 3.2 and 3.3 are dedicated to data clustering and to data mining specifically on Twitter [1].

3.1 Self-Organizing Maps

Self-Organizing maps are used in a wide are of applications, from authentication systems [9] through network intrusion detection [30] and speech recognition and analysis [17]. We now highlight some of their applications.

3.1.1 The Geo-Som

The Geo-SOM, by Bação et al. [3], applies the first law of geography “Everything is related to everything else, but near things are more related than distant things.” to the SOM algorithm. In this case, the winning neuron is chosen in a radius defined by the geographic-coordinates of the data, forcing units that are close geographically to be close in the output space.

The algorithm works by defining a variable k which is used as a ”geographical tolerance” that forces the winning neuron to be geographically near the input pattern. When $k = 0$ the BMU is forced to be unit geographically closest to the input data, whilst when k increases, the tolerance for other data geographically further is tolerated. k is a geographic radius applied in the output space, when the radius exceeds the size of the output space every unit is eligible to be the winning neuron and therefor we have a regular SOM.

The selection of the BMU is done in two steps. First geographic neurons inside the tolerance k with the input data as a center are selected, only after that comparisons are made with the rest of data present in the input data. The representation of the Geo-SOM can be seen in Figure 3.1, where the units considered for the best match are defined by a sort of geographic radius defined by k, whilst the original SOM the BMU could have been any of the units presented on the figure.

The Geo-SOM approach to the alteration of the default SOM algorithm is specially interesting due to the fact that this thesis objective is also to give relevance to data patterns that are not located in the same space as the trained data. In a way what we are trying to achieve is similar to the work by Bação et al. [3] but changing the geographic relevance in data by a social relevance.

3.1.2 Detecting Hidden Patterns on Twitter Usage

Cheon and Lee [8] analyzed hidden patterns in the usage of twitter. In this study they started by collecting data from the twitter API of different kinds of topics like ”2009 Iran Election” and ”iPhone 3.0 OS launch”. They made multi level signal extraction not only from information directly

[1] http://www.twitter.com

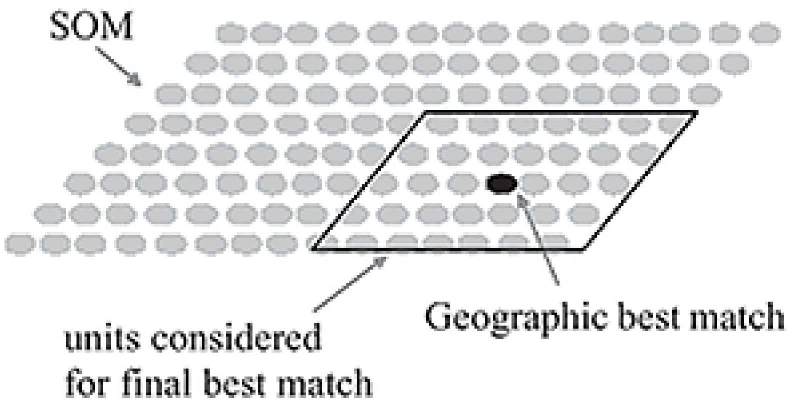


Figure 3.1: Geo-SOM structure, where the units considered to be the BMU are constrained by the geographic coordinates of the data, from Bação et al. [3]

present on the tweet, but also by cross referencing with other social websites and with the twitter user profile information. The signals retrieved from the social network can be seen in Table 3.1.

Table 3.1: Twitter Signals

Twitt Corpus
Tweet Size
Replies
Re-tweets
Hashtags
Presence of URIs and Type of linked content
Type of Device
Tweet Location
Twitter Profile
Account Age
Gender
Country
frequency of posts
Friends to followers ratio
Number of customizations
External Sources
Other Social Network Accounts
Type of website

Parece me interessante descrever quais as caracteristicas diferenciadoras dos clusters. By applying a SOM, they could find 4 demographical clusters during the Iran 2009 Election. The first cluster was characterized by young web-based Iranians, with twitter accounts not older than 3 months with a high frequency of replies. The second cluster was mainly compound of web users from Iran accounts older that 3 months. The third cluster had Iranian users with mobile clients with large texts clearly trying to raise awareness. The fourth and final cluster represented the users around the world trying to raise awareness about the issue by sharing tweets with URIs. Looking at their analysis about the topic ”2009 Iranian Election” it is clear to see that it was possible to describe the type of users represented in the social network and the way they interact with it.

On the iPhone 3.0 OS launch it was possible to find three main clusters. The first cluster was characterized by male users, accounts older than 90 days, coming from countries where the iPhone is marketed, with high adoption of social media clearly representing the target market of the iPhone or its customers. The second cluster had new accounts with higher rate of followers to followees, high frequency of posts per day, presence of URI linking to technology blogs or websites, no country or gender specified meaning that this cluster was clearly composed by news aggregators and technological news websites. Inside the second cluster there was a sub-cluster of Japanese users which represents the high rate of iPhone adoption in Japan. Finally the third cluster was clearly spammer accounts that where eventually deleted after a couple of months, characterized by popular social connections, posting more than 50 tweets a day with external URIs and the accounts where not older than a day or so.

In conclusion it was possible to detect Twitter usage patterns and specifically detect spammers before they where banned from the social network.

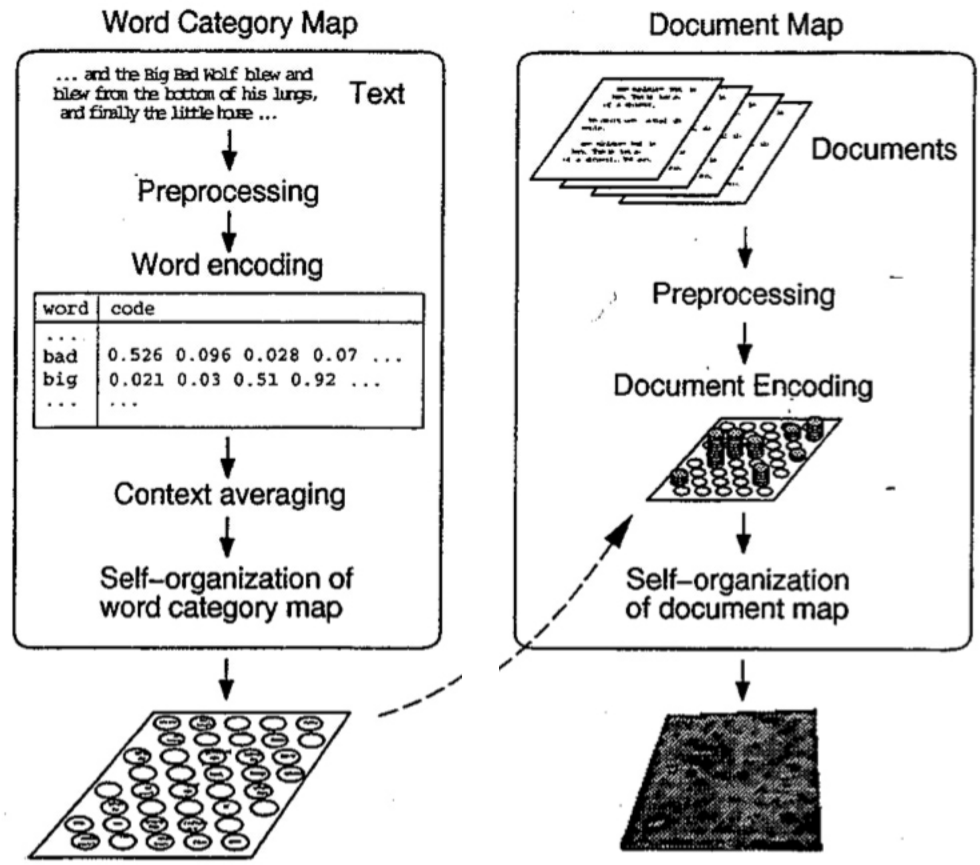
3.1.3 WEBSOM

Honkela et al. [11] developed a new approach to automatically order arbitrary, free from textual, document collections, using two different SOMs. The first SOM is called word category map an its used to find words that have similar meaning, while the second SOM, called document map, is the one actually used to cluster the documents.

The WEBSOM was not based on keywords and Boolean expressions, instead, words with the same meaning are encoded in a word category map (Fig 3.2(a)), where placement and frequency in documents is taken into account. This way it is possible to remove words with similar meaning, greatly reducing the VSM size and thus making it possible to train the document map in scalable way.

3.2 Topic Detection and Tracking with Clustering

Allan [1] defined Topic Detection and Tracking (TDT) as: ”TDT research begins with a constantly arriving stream of text from newswire and from automatic speech-to-text systems that are monitoring selected television, radio, Web broadcast news shows. Roughly speaking, the goal of TDT is to break the text down into individual news stories, to monitor the stories for the events that have not been seen before, and to gather stories into groups that each discuss a single news topic”



(a) The word cathegory map, a SOM where word frequency and placement is used for encoding text

(b) The document map, organized based on documents enconded with the word cathegory map.

Figure 3.2: Basic architecture of the WEBSOM method, from [11]

Nowadays due to the rapid adaptation of people to always be on-line, through the usage of cellphones on the move, desktops at work and even TV at home, the increase of user generated content has increased tremendously in latest years. In 2006 35% of on-line adults and 57% of teenagers created content on the Internet [2], which in "Internet Years" was ages ago.

The challenge of TDT is evermore focused on online generated documents, and in new forms to be able to track and categorize all the information that is continuously being generated. Many TDT techniques have been proposed, a significant amount of them rely on the Term Frequency–Inverse Document Frequency (TF-IDF) [4] which is not particularly adequate for topic detection on Twitter, due to the fact that tweets are very small, often with by typos or slang words and might be written in multiple languages, sometimes on the same tweet. In this subsection we will take a look at multiple methods of topic detection in general and specifically on the Twitter social network.

3.2.1 Topic and Trending Detection

Cataldi et al. [7] propose a new technique for emerging topic detection that permits real-time retrieval of the most emergent topics expressed by a community on Twitter. Their work applies the PageRank algorithm [28] to the users follower/followee relationship in order to find the most influential users on the network. It then calculates the most trending topics by relating, social influence, word co-occurrence and time frame. In the end, an interface was created where it would be possible to navigate hot topics in a given time frame. Topic labeling was not automatic and was implicit by the time frame of an event.

Weng et al. [32] also used the PageRank algorithm to find the most influential twitter users on a certain topic. However using a different approach, they represent each twitter user as a bag of words comprising of all the tweets that they have posted, and apply Latent Dirichlet Allocation (LDA) [5] in order to find the topics each user is interested in. In the end it was possible to prove that follower/followee relations on twitter are not just casual, but that people actually follow other people to whom they have some resemblance or common interest. This concept is called homophily and will be further explored by this project.

3.3 Twitter Data Mining

In this subsection, we will focus on work done on the Twitter social network in order to leverage insights on how the public data available from the website can be explored.

[2] Data source: http://www.pewinternet.org/Presentations/2006/UserGenerated-Content.aspx

Table 3.2: Tao et al. [31] tweet characteristics hypotesis versus influence

Hypotheses	**Influence of Features**
Syntatical	
Tweets that contain hashtags are more likely to be relevant than tweets that don't	Not Important
Tweets that contain an URI are more relevant that tweets that don't	Important
Tweets that are replies to other tweets are less relevant	Important
The longer the tweet is the more relevant it is	Not Important
Semantic	
The more the number of entities the more relevant a tweet is	Important
Different types of entities are of can have different amount of interest to a give topic	Important
The greater the diversity of concepts mentions in a tweet the more likely for it to be relevant	Important
The relevance of a tweet is determined buy its polarity	Important
Contextual	
The lower the temporal distance between a query and the creation of a tweet the more relevant the tweet is	Not Important
The more the number of tweets created by a user the more relevant one of his tweets will be	Not Important

3.3.1 Tweets Implicit Data

Tweet retrieval and analysis is a double edged problem. On one side the tweet is really small, which makes it almost impossible to retrieve any actual sense from it. On the other hand the amount of tweets generated per day is around 140 million[3] wich means that it is very hard to do a deep analyses of the semantics and content of individual tweet, and that only the more appropriate signals should be evaluated. For this reason Tao et al. [31] evaluated how the multiple signals that could be retrieved, directly or indirectly, from the tweet corpus could mean that a tweet is relevant for a determined topic. In his work, Tao presents premises that seem intuitively true and proves they actually are relevant through a comparison of multiple precision and recall values.Their results on feature comparison are summarized in Table 3.2, the first column consists of all the made hypothesis categorized by type, and the second column tells if the data used actually influenced in precision and recall results. Tao also compared result of topic characteristics, concluding that distinction between local and global events as well as temporal persistence proved to not be relevant on relevance prediction.

McCreadie and Macdonald [24] also approached the issue of having very little content on tweets in order to categorize a tweet, and tried to solve it by applying the content of linked URIs into the tweet body in order to improve precision and recall. The best fitting approach was using Field-Based weighting, where for each tweet a new document is created which contains two fields; the terms in the tweet and the terms in the linked document. Afterwards a learning to rank algorithm called PL2F [23] is used against the dataset from Microblog2011 in order to find the

[3]https://blog.twitter.com/2011/numbers

best weighting. With this model they where able to improve precision in an order of 0.9, over only analyzing the text contained in the tweets.

3.3.2 Tweeter Natural Language Processing

Using standart NLP tools on tweets has been extremely unreliable, due to the fact that microbloging text tends to be full of abbreviations, emojis and smiles . Recently Owoputi et al. [27] publish an NLP library specific for twitter. As shown in Figure 3.3 ARK Tweet NLP can tag words that are only used in social networks. The tagger was built using maximum entropy Markov model where a tag is assigned to a word based on the entire tweet text, and the tag assigned to the word to its left. Owoputi et al. [27] states that the tagger has a 93.2% accuracy. By using NLP tools, it is possible to reduce the dimension of VSM space by only choosing words that are relevant like common nouns, hashtags and proper nouns. This will not only will yield better results by removing tweets that have no content whatsoever and therefor cannot be categorized, but will also increase performance during training due to the reduced dimensions caused by less use of words.

ikr	smh	he	asked	fir	yo	last
!	G	O	V	P	D	A
name	so	he	can	add	u	on
N	P	O	V	V	O	P
fb	lololol					
^	!					

Figure 3.3: Tweet automatically tagged with ARK Tweet NLP. ! stands for interjection, while V stands for verbs and D for determiner. The full table of tags can be found in [27].

3.3.3 Rapidly Changing Trends

Due to the real time nature of Twitter, using typical retrieval model that relies on term frequency models like Okapi BM25 or language modeling cannot be applied, as stated by Lin and Mishne [21]. The study of topic endurance on the social network proved that topics are presented in bursts of queries and mentions. In addition the typical usage of twitter for search is not the same of Google. When users are searching on twitter they want to find out what is happening right now, meaning that classification techniques based on past events cannot respond this kind problem. As stated by Lin and Mishne [21] this problem has not yet been solved at Twitter (or anywhere else at the time of writing this report), and issues a new kind of data analysis approach that was not taken into consideration in the past.

This effect of rapidly changing topics and queries based on real time events was named ”Churn”, and can be clearly seen in Figure 3.4.

By including social features into clustering algorithms we think that it will be possible to discover new clusters of topics that have greater significance to the users of social networks. Also part of

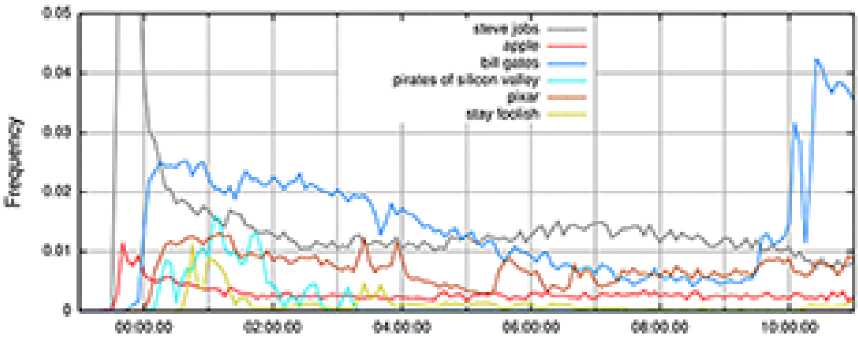


Figure 3.4: The Churn effect: Frequencies of queries related to Steve Jobs death over a 12 hour period in 5-minute intervals, normalized to the total number of queries in the interval. At its peak, the query “steve jobs” reaches 0.15 (15% of the query stream); Graph taken from [21]

the churn effect might even be reduced due to the fact that the information that is closer to a user will be considered more relevant than just the words that comprise the data.

3.4 Summary

Ending section summarizing the chapter is typically a good idea.

Ensure that the next chapter starts in a odd page

4

Clustering Tweets with Self-Organizing Maps

```
{
  "_id" : { "$oid" : "4fa14bc97e5617025fb14787" },
  "text" : "RT @FastCoDesign: A Paintbrush That Works On The iPad
      http://t.co/eWjEZAga (@sensubrushman)",
  "id_str" : "197701817864421376",
  "coordinates" : null,
  "in_reply_to_screen_name" : null,
  "in_reply_to_user_id" : null,
  "possibly_sensitive" : false,
  "favorited" : false,
  "in_reply_to_status_id" : null,
  "source" : "<a href=\"http://www.flipboard.com\" rel=\"nofollow
      \">Flipboard</a>",
  "possibly_sensitive_editable" : true,
  "contributors" : null,
  "retweet_count" : 0,
  "truncated" : false,
  "in_reply_to_status_id_str" : null,
  "geo" : null,
  "in_reply_to_user_id_str" : null,
  "entities" : { Enteties Object },
  "user" : { User object },
  "retweeted" : false,
  "id" : 197701817864421376,
  "place" : null,
  "created_at" : "Wed May 02 14:59:21 +0000 2012" }
```


Figure 4.1: JSON representation of a Tweet.

Tweets cathegorization with **SOMs!** (**SOMs!**) requires a dataset to work on. Due to sistematic API restrictions, which where implemented in order to protect Twitter business model, gathering a dataset that directly maps to the social network is a great chalenge by itself. In order to cathegorize tweets with **SOMs!** first we used a dataset provided by INESC-ID. The dataset had almost 1TB of data in JSON format.

Each tweet is comprised of multiple paramters. Figure 4.1 shows how a tweet is represented in JSON format. Inside the tweet there is also information about the user whom created the tweet, shown in Figure 4.3 and enteties shown in Figure 4.2.

As can be seen in Figure 4.3 no information about the social relations of the user which emited the tweet are present. Therefor in order to retrieve the social network in which a user is contained, it will be necessary to connect to the Twitter API. Crawling twitter is discussed in further depth in Chapter 5.

In order to better understand the dataset at hand, all the JSON files where converted into CSVin a way to reduce the size of the dataset. While tweets where being converted, Uniform Resource Locator (URL) where removed due to the fact that most of them where minified in order to fit in less that 140 characters. Also, all tweets that where not identified as being in english where

```
{ "user_mentions" :
  [{ "indices" : [ 3, 16 ],
    "id_str" : "158865339",
    "name" : "Co.Design",
    "id" : 158865339,
    "screen_name" : "FastCoDesign" },
  { "indices" : [ 76, 90 ],
    "id_str" : "534544812",
    "name" : "Matt",
    "id" : 534544812,
    "screen_name" : "sensubrushman" } ],
  "urls" :
    [ { "url" : "http://t.co/eWjEZAga",
        "indices" : [ 54, 74 ], "display_url" : "bit.ly/IAaKQf",
        "expanded_url" : "http://bit.ly/IAaKQf" } ],
  "hashtags" : [] }
```

Figure 4.2: Enteties mentioned inside the tweet

also removed. The tweet shown in JSON format in Figure 4.1 is converted to CSV in Figure 4.4.

Identifying tweets that where not in the english language was done through the usage of Ruby library called whatlanguage [1], which tries to identify one language through Bloom Filters. Inside the tweet there is a field which identifies the user language, we found that x is not acurate. Removing tweets that weren't in the english language reduced the amount of different words in x and therefor will reduce the dimensional size of the SOM.

The initial dataset features is described table x .

Work done on the INESC twitter dataset with SOMs. SOM implementations used, what where their strong points and weaknesses SVM Dimension reduction and text treatment: compare multiple aproaches to reduce the svm size of tweets without losing relevant information

[1] https://github.com/peterc/whatlanguage

```
{ "default_profile_image" : false,
  "friends_count" : 277,
  "profile_link_color" : "0084B4",
  "followers_count" : 105,
  "url" : null,
  "profile_image_url" : "http://a0.twimg.com/profile_images/690647919/19335_266330051104_635886104_3750428_5949465_n_normal.jpg",
  "id_str" : "26549290",
  "following" : null,
  "favourites_count" : 7,
  "notifications" : null,
  "profile_background_color" : "C0DEED",
  "statuses_count" : 331,
  "profile_background_tile" : false,
  "profile_background_image_url_https" : "https://si0.twimg.com/profile_background_images/79871480/DSC09031_2.jpg",
  "description" : "A Chicago-based designer and educator fascinated with the power of design to ignite change \r\n\r\n",
  "location" : "Chicago",
  "contributors_enabled" : false,
  "geo_enabled" : false,
  "time_zone" : "Central Time (US & Canada)",
  "profile_sidebar_fill_color" : "cde2e6",
  "listed_count" : 2,
  "profile_sidebar_border_color" : "C0DEED",
  "default_profile" : false,
  "show_all_inline_media" : false,
  "verified" : false,
  "protected" : false,
  "is_translator" : false,
  "profile_use_background_image" : true,
  "profile_image_url_https" : "https://si0.twimg.com/profile_images/690647919/19335_266330051104_635886104_3750428_5949465_n_normal.jpg",
  "name" : "Karma Dabaghi",
  "follow_request_sent" : null,
  "lang" : "en",
  "profile_text_color" : "333333",
  "id" : 26549290,
  "profile_background_image_url" : "http://a0.twimg.com/profile_background_images/79871480/DSC09031_2.jpg",
  "utc_offset" : -21600,
  "created_at" : "Wed Mar 25 17:55:26 +0000 2009",
"screen_name" : "karmadabaghi" }
```


Figure 4.3: JSON representation of a user, inside a tweet.


```
karmadabaghi,A Paintbrush That Works On The iPad @sensubrushman
```


Figure 4.4: CSV representation of a Tweet. The username is present in the first column and the tweet text on the last.

5

Crawling Twitter for Social Relations

Explain the limitations of the INESC tweet dataset: crawlled by hashtag, social connections can only be obtained through connections to the twitter API, a lot of the tweets had no active users etc.

6

SOM Framework

Explain what got me to create my own ruby library: everybody is making their own SOM algorithms (ex.: websom, hsom etc). Most implementations want to get as close to the metal as possible in order to deliver faster trainings, which makes the lybraries hard to modify. SOM framework is an modular implementation of the SOM algorithm in an higher level programing language which makes it easier to construct and test new SOM algorithms.

7

Homophilic SOM

The default SOM algorithm has no idea whatsoever of the social connections between the tweets, it simply looks at the binary vectors that represent sentences and assigns it to the most similar neuron.

In order to better categorize socially connected data, we propose some alterations to the SOM algorithm in order to make it aware of the social connections between the tweets, and therefor better represent the homophilic behavior present on social networks.

8

Changes in the output space

The outputs space is the zone on the SOM algorithm where the neurons reside. It works like a cortex where neurons are scattered in a geometric fashion, generally a square. The output space is generally initialized with random values, with a relatively high learning rate, and also a relatively high number of epochs. The algorithm is made this way in order to be able to identify any type of data that can be represented as vectors. First we will try to change the output space to better resemblance the social network.

9

Evaluation Metrics

Contents

- show UMatrixes and multiple steps map trainning of the SOM library trainnig
- show metrics for the crawller, tweets per second, users persecond, size of the dump a long the time.
- compare my som library with other som libraries: training velocity with diferent parameters, map after trainned.
- Compare Homophilic-SOM results with non homophilic: UMatrixes, cluster results, Quantization error, jacknife.

Evaluation of the topic detection on Tweets will be made in two distinct ways. The first way will focus on binary classification using the precision and recall metrics, and will be described in Subsection **??**. The second way will focus on statistically testing the SOM learning process and the computed trained network. This testing process will be described in Subsection **??**.

9.1 Testing for Precision and Recall

Precision and Recall are both ways to measure the rate of right guesses made by the trained SOM network, and are defined in the following way:

- **Precision:** Fraction of retrieved instances that where relevant

$$precision = \frac{|relevant\ documents \cap retrieved\ documents|}{retrieved\ documents} \tag{9.1}$$

- **Recall:** Fraction of relevant instances that where retrieved

$$recall = \frac{|relevant\ documents \cap retrieved\ documents|}{relevant\ documents} \tag{9.2}$$

In order to calculate Precision and Recall we need to have the relevant documents and the retrieved documents. The relevant documents are rather hard to determine because they need to be categorized by humans, which is an expensive task.

9.2 Statistically Testing the SOM

SOM training is always subject to some variability due to multiple causes, like the sensitivity of initial conditions, convergence to local minima and sampling variability, as stated by Bodt et al. [6]. This subsection will present statistical tools to measure the quality of the SOM, by measuring its quantization error and topology preservation.

9.2.1 Quantization Error

The SOM Quantization Error is the mean of all Euclidean distances between the observed data points and their corresponding winning neuron. This value might vary depending on the initialization neurons or the order of the input data fed into the SOM while the training is occurring. When applied to an individual input data, represents how well a neuron is representing input data. Since the SOM Quantization Error represents the mean of all quantization errors from all the input data, generally, the lower the error is the best the SOM was trained.
No general formula exists to minimize quantization error [6] . What is generally done is just to change the number and values of the starting neurons and the order of the input data in order to train multiple SOMs. In the end the SOM with the lowest quantization error is chosen. In this project since multiple approaches to the SOM algorithm and data representation will be tested, as described in Section **??**,and the ones having the lower quantization error will be selected for the prototype.

9.2.2 Topology Preservation

The Self-Organizing Map performs a mapping from the n-dimensional input space into the two dimensional output space and where resides one the most fascinating characteristics, which is that the output map tries to preserve the topology from the input space. This grants the SOM algorithm a way to visualize high-dimensional data that other neural networks or clustering algorithms don't have. Even though this is true, sometimes during training it is not possible to preserve the topology of the network. Thus topology preservation can be measured through the Topographic error Kiviluoto [15] which is the proportion of all data vectors for which first and second BMUs [1] are not adjacent units. In this project the Topographic Error will be calculated for all SOM implementations and VSM usages in order to understand if the representation of the SOM output space is well defined.

9.3 Conclusions

[1] unit that is closest to the winning neuron. BMU Best fitting unit

10

Conclusions and Future Work

Draw your conclusions here and sell your work. Trasmit to the juri how hard it was to develop the presented work.

A future work section is usually here.

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A

Appendix A

B

Appendix A