Sentiment Analysis on Twitter : Effects in a Social Network

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Our purpose is to build a powerful platform for real-time data analysis of tweets on twitter trends. We also want to analyse all the tweets of 2017 based on a downloaded sample of data (average of 6 To). All this data analysis will be accessible via a web interface that will be developed. We want to build a powerful system of sentiments analysis by making a database structure of tweets which is relevant about impacts and effects. The system should provide a faster way to execute Machine Learning methodologies behind data extracted from Twitter. Analysis news actuality by getting an analysis on actual trends with real stream data by building an efficient web interface to get results easily and build a system without false accounts and keep a control on data continuously.

Categories and Subject Descriptors: H.2.8 [**Database Applications**]: Big Data and Real Stream—*Cloud Computing*; I.3.7 [**Learning**]: Apache Spark and Hadoop—*Social Media Analytics*

General Terms: Twitter, Psychological Profile

Additional Key Words and Phrases: Data Mining, Natural Languages Processing, Sentiment Analysis, Classification, Text Mining,Convutional Neural Network, TensorFlow

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1. INTRODUCTION

The main subject is Sentiment Analysis on Twitter[1], a microblogging platform where people can easily share their thought on anything and their habits too. We have a lot of publications on sentiment analysis but not so much research about impacts and their effect on society. The maximum characters are 140 which can be a good thing for the process of analysis because it will make it faster in a way to perform on small messages but in the other hand we should pay attention on accuracy of results. Even its an enormously continuous stream of data, Twitter is a good extra sentiment though an online community. Therefore, how to optimize all this streaming data and build a web interface for users who want to get data. We will use in our project will use many methodologies from Machine Learning like unsupervised methods to make a classification of sentiments, and supervised method to predicate psychological profile. Finally, one big step will be and efficient system about control of massive data incoming, a check on false account and spam messages that will destroy our results for example.

> The best way to engage honestly with the marketplace via Twitter is to never use the words "engage," "honesty," or "marketplace."
>
> (Jeffrey Zeldman)

In this study, we introduce to the readers, a problem of Data Processing and Cloud Computation, which have been rapidly a trend over the last decade.

2. RELATED WORK

To begin, ye can refer to this article [Themis Palpanas and Mikalai Tsytsarau 2011] because we can relate that it is a point of start, it gives us a theoretical review on the development of Sentiment Analysis. The interested reader can also refer to previous surveys in the area, like [Öztürka and Ayvazb 2017] for their data process about tweets in Turkish and English because most of free API have their functionnality in English. We also base on a previous work of [Gupta et al. 2017], that helped us on machine learning techniques but they did not implement a real stream functionnality on their publication as we did, because they only use Tweepy and store their tweet fetched from it. One of the publication that helped us to analyse only English tweets was the W2VLDA and the work of [Aitor García-Pablos 2017], they clearly have better results on English tweets. As an active research field that has emerged for a long time now, sentiment analysis is now been greatly implement but it is also with a cost (for example, IBM Watson Tone Analyzer). Sentiment analysis is a discipline that extracts peoples feelings, opinions, thoughts and behaviors from users text data using Natural Language Processing (NLP) methods. For methodologies on preprocessing, and feature generation, we based our work on process. Then we can also cite for a reason, they removed numbers from theirs tweet thinking that in general, numbers are of no use when measuring sentiment and are removed from tweets to refine the tweet content but we wanted to keep them thinking the contrary. We had over 800 million tweets in English and all that data to analyze where possible just because of the MapReduce Model in majority but there also a weakness for this model in our case. We will now make a comparison between Machine Learning methods and the results obtained in the following publication: (quote the Greeks) with our methods and the results we obtained. In this publication, the authors proceeded in two steps: A binary and tertiary classification. For the first, they retrieved a dataset of 1.5m of labeled tweets (positive and negative) that they divided into seg-

[1] https://twitter.yannistannier.io/#/dashboard

Jason Scott Sadofsky acknowledges a Jason Scott, is an American archivist, historian of technology, and film-maker. Archive Team is a group dedicated to preserving digital history that was founded by Jason Scott in 2009. Data was collected from the website of The Archive Team.

DOI:http://dx.doi.org/

ments (1000.2000.5000.10000, 15000, 20000, 25000). Each segment was then transformed into a vector of unigrams. They then applied 2 ML algorithms: Naives Bayes, Logistic regression, decision tree. For tertiary classification, the authors retrieved a dataset of 12,500 labels and applied the same algorithms. In the case of this publication, we wanted to test something else. We retrieved the same dataset as in the publication. First of all, we did a lot of preprocessing of the data to remove uppercase letters, punctuation, and so on. We then perform a Lemmatization on the dataset to group the words of the same family. Once the data set was processed, we transformed it into term documents (CountVectorizer) and we applied a tf-idf weighting. We then used the same 3 algorithms as in the publication to which we added others in order to have a better overview.

3. CLOUD COMPUTING

Cloud computing was used for the project with Amazon Web Service (AWS) for helping developer making machine learning built systems quickly. Amazon Elastic MapReduce is a cloud-based Hadoop solution that Amazon has been offering since 2009. It is hosted on Amazon EC2's scalable cloud infrastructure and leverages the Amazon S3 storage service. The main interest of such a service in cloud mode is its elasticity. There is no need to plan in advance the necessary processing and storage capacity, this can be increased on the fly and the pricing is based on the resources actually consumed. An exemple, with Brown clusters can really be usely [Felipe Bravo-Marquez and Eibe Frank and Saif M. Mohammad and Bernhard Pfahringer 2016] in cloud computing service du to this complexity of this hierarchical clustering of words based on the contexts. Some of the potential disadvantages to be aware of are the high latency times for I / O on S3, which is inevitably greater than on a Hadoop home installation. Some of the scripts (see repositories) were launched on desktop, the config used at was:

—i7 6700K @4.20Ghz

—16GO DDR4 @2400Mhz

—NVIDIA GTX 1060

—128Go SSD / 3TO HDD

—Debian 9.4 (Stretch) kernel version: 4.9.0-6-amd64

For the read operations, the SSD was used to load the JSON files by hundreds or thousands, later calculations, the recording will be done on the HDD.

3.1 MapReduce Model and Spark Framework

In 2015, Spark was used in more than one thousand Airbus companies at Toyota, Netflix or EBay. Spark is a distributed computing framework. MapReduce [Alexandros Baltas and Andreas Kanavos and Athanasios K. Tsakalidis 2017] as they explain undertheir Cloud computing section, greatly simplified Big Data [Garg and Chatterjee 2014] analysis on large clusters of machines that could fail. But MapReduce has become a victim of its success users are always asking more with applications, such as iterative operations (ML for example) or interactive operations (several requests is not suitable) for these types of operations. The only way for MapReduce (for example, two steps of the same algorithm) is through stable storage, physically writing to HDFS for example. But writing on a large volume of data data on HDFS is already taking a long time since it is necessary to replicate this data to be able to cope with any failures and to reload several times the same data from HDFS in the following jobs will be very slow. An algorithm that repeats the same operation in a loop will therefore quickly have a prohibitive calculation cost in MapReduce. Some Hadoop MapReduce applications thus pass the priority of their execution times on read and write operations.

4. METHODOLOGY

First, we will talk about scripts using Spark with Scikit-learn and TextBlop. Scikit-learn provides us with efficient tools for data mining and data analysis, its usable in various contexts and can be downloaded on their website as an open-source program. TextBlob is a library for processing textual data with natural language processing (NLP) [Hassan et al. 2012] tasks such as sentiment analysis, classification, translation, and more. TextBlop use Google translate [2] for sentences that are not in English, so in free and anonymous usage are limited 1000 words/day which is why we could not have analyzed every tweet on the database. The Spark Python API (PySpark) exposes the Spark programming model to Python. We used it because it simpler and we have a gain of productivity against language such as Scala (In some cases like counting the number of languages or doings some basic statistics we used Scala, source is available in the Github repository of the project) or Java. Python is dynamically type, so RDDs can hold objects of multiple types. To run all those libraries, we used Amazon EMR, an Amazon EMR. For the real-stream part, we created a module for Data Stream with Kinesis [3] and MQTT. We used a StreamListener that will permanently get data from Twitter and a consumer which analysed each tweet with TextBlop and Scikit-Learn. MQTT is a publish-subscribe messaging protocol based on the TCP / IP protocol, it was originally developed by Andy Stanford-Clark (IBM) and Arlan Nipper (EurtoTech), then offered to the Open Source community (For information, MQTT v3.1.1 is now an OASIS standard). We developed the website using React.js, we could design simple views for each state in our application, and React efficiently update and render just the right components when your data changes. Text from tweets are inherently noisy. They contain twitter specific words along with hashtags and username mentions. Cleaning the text before further processing helps to generate better features and semantics [Hassan et al. 2012]. Machine learning approach relies on statistical algorithms in one hand to solve the Sentiment Analysis as a regular text classification problem that makes use of syntactic and/or linguistic features. Text Classification Problem Definition: We have a set of training records D where each record is Sentiment analysis algorithms and applications: A survey labeled to a class. The classification model was written in Python and we used TextBlop for sentiment analysis. Then for a given instance which mean an input of tweet coming via a StreamListener with Kinesis or in the Archive of unknown class, the model is used to predict in what label it should be. The hard classification problem about tweets is that we cant really be sure about results only if tweet were confirmed by a human being or every user of Tweeter will have to add information like sentiment and emotion for his tweet before sending it but, how can we be sure it is true?

[2] https://github.com/mbenhamd/twitter-sentiment-analysis/tree/master/gtranslate_module

[3] https://github.com/yannistannier/twitter-sentiment-analysis/tree/master/kinesis-realtime

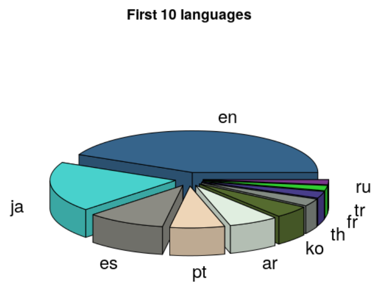

Fig. 1. Results for 1 208 516 638 tweets analysed (deleted tweet was not count).

4.1 Pre-Processing

In this paper we introduce two new resources for pre-processing twitter data [Zhao Jianqiang and Gui Xiaolin 2017], we used some of their ideas like removing URL, as you can see in the repository, an emoticon dictionary is available in Python and we can remove them from any tweets.Unsure and irrelevant label was not used for this classfication [Poddar et al. 2016] because we think that it is more relevant to detect bots and not adding them into the analyse process rather than put a tag on them and lose time of computation for sentiment analysis. It is powerful because even it is relevant, we cant take them for computing them after due to a problem of time. Positive, Negative, and Neutral are the three labels for Sentiment Analysis and Joy, Fear, Anger, Surprise and Sadness are the fifth labels for Emotion Analysis. We pre-process all the tweets as follows: 1) We remove all the emoticons 2) We remove all URLs with a regular expression 3) Replace targets (e.g. @John) by also removing them 4) Removing RT for most of the tweet, because it doesnt mean something for the application. Tweets in a general way contain a lot of opinions but they are expressed in different ways by users, as they did [Apoorv et al. 2011] by keeping emoticons. It deals with the preparation that removes the repeated words and punctuations and improves the efficiency the data. Forward other process is doing like converting upper case to lower case. User names and URLs are not important from the perspective of future processing; hence their presence is futile. All usernames and URLs are removed to improve increase the real result.

4.2 Machine learning for Emotion and Sentiment classification

In order to predict the feeling (Postive, negative, neutral) and emotion (joy, anger, sadness, fear,surprise) for each tweet, we used 2 methods. They used other label for emotions that we did not To determine the feeling of the tweet, we used the TextBlod librairy which provides a simple API of Natural Languge processing and thus allows us to make the sentiment anlysise. For this, Textblob calculates a Polarity rate of -1 to +1 or -1 corresponds to an extremely negative twitch and an extremely positive +1. To determine the emotion, we had to create our own classification model (classification in English what) with scikit-learn. To do this we took a tweet dataset that we labalised (after having data cleaned as indicated in the previous paragraph) thanks to indico. We then transform this dataset into a term document matrix and apply a TF-IDF standardization to evaluate the importance of the term content in each tweet. Finally we applied a SVM for the classification because like they said [Walaa Medhat and Ahmed Hassan and Hoda Korashy 2014], it is very suitable for text data. Once the model was extracted, we used it with spark to predict the emotion of all the tweets.

5. DEEP LEARNING

5.1 Data Processing and Architecture

First, we downloaded the dataset of 1 578 627 tweets preclassified, then we read the dataset from the csv into two files (.pos and .ned) with (see csv_parser.py). Then we generate a CSV with the vocabulary (and its inverse mapping) with an another process. Each vocabulary has a weight. For example if a name is wrote, we remplace it by <NAME/>and the same thing for a link : <LINK/>. The network implemented in this script is a single layer CNN structured as follows:

—**Embedding layer**: takes as input the tweets (as strings) and maps each word to an n-dimensional space so that it is represented as a sparse vector (see word2vec).

—**Convolution layers**: a set of parallel 1D convolutional layers with the given filter sizes and 128 output channels. A filter's size is the number of embedded words that the filter covers.

—**Pooling layers**: a set of pooling layers associated to each of the convolutional layers.

—**Concat layer**: concatenates the output of the different pooling layers into a single tensor.

—**Dropout layer**: performs neuron dropout (some neurons are randomly not considered during training).

—**Output layer**: fully connected layer with a softmax activation function to perform classification.

5.2 TensorFlow

TensorFlow is an open source machine learning tool developed by Google. The source code was opened on November 9, 2015 by Google and released under Apache license. It is based on the DistBelief infrastructure, initiated by Google in 2011, and is equipped with a Python interface. TensorFlow is one of the most used tools in AI in the field of machine learning. We used an architecture based on previous work (here). Even we used a GTX 1060 (1212 cuda cores compared to the Titan V which was developed for Deep Learning with 5120 cuda core), it took 2h20 to train the CNN. The course of the exection is available in the file "log.log" The neural network weighs about 424.1 MB. You can download in JSON or CSV format the results for the validation of the training loss (here).

The graphics below can be found thanks to the TensorFlow web interface. To summarize 110990 (epoch 10), validation accuracy: 0.825287, loss of training: 49.6865

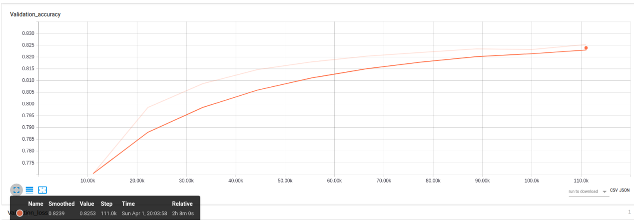

Fig. 2. Schema of Validation Accuracy From TensorFlow Interface Web.

We can see a logarithmic evolution of the accuracy of the neuron network, 82% is in itself a mean result in the sense that neuron methods are expected to be accurate to 95% minimum in practical cases. For the text classification case, 1.5 million tweets do not contain enough vocabulary per se to allow large-scale use.

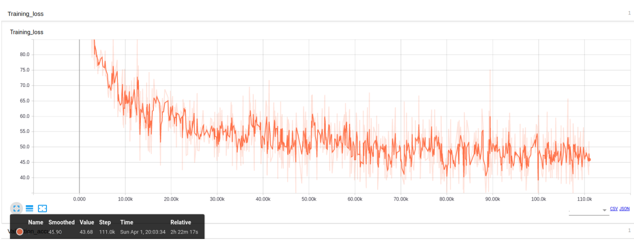

Fig. 3. Schema of Training Loss From TensorFlow Interface Web.

The validation loss here is 49.68The lower the loss, the better model (unless the model has over-fitted to the training data). The loss is calculated on training and validation and its interperation is how well the model is doing for these two sets. Unlike accuracy, loss is not a percentage. It is a summation of the errors made for example in training or validation sets. In the case of neural networks, the loss is usually negative log-likelihood and residual sum of squares for classification and regression respectively. Then naturally, the main objective in a learning model is to reduce the value of the loss of the value of the product. Loss value implies a certain model behaves after each iteration of optimization. Ideally, one would expect the reduction of loss after each, or several, iteration (s). The accuracy of a model is usually determined by the model parameters and is determined. Then the test samples are fed to the model and the number of mistakes (zero-one loss) the model is recorded, after comparison to the true targets. Then the percentage of misclassification is calculated. For example, if the number of test samples is 1000 and model classifies 952 of those correctly, then the model's accuracy is 95.2

Here is a summary of training loss and validation accuracy (done with Spark with the describe function).

Table I. Training Loss describe

Summary	Wall Time	Step	Value
$Mean$	1.59x10^9	552 51.293	56.1645
$Stddev$	2470.404	32 058.352	22.553
Min	1.52x10^9	100 157	102.860
Max	1.52x10^9	99 954	97.983

Table II. Validation Accuracy Describe

Summary	Wall Time	Step	Value
$Mean$	1.59x10^9	65585.818	0.81360
$Stddev$	2701.1972	35258.454	0.01645
Min	1.52x10^9	11 099	0.7704
Max	1.52x10^9	99 891	0.8252

Validation accuracy is a good practice. To conclude, as you can see, the previous work had a final validation accuracy of 0.80976, and a validation loss of 53.3314, one of the reseaon here it may be because we did more epochs so the network could more train (we do not have information about their initial configuration).

5.3 Feature Generation

Take the example of a two-step algorithm, MapReduce will have to perform two jobs: At the first job: 1. Read the initial data. 2. Execute step 1 in a first job. 3. Save the intermediate result in a distributed way In the second job: 1. Read this result 2. Execute step 2 3. Save the result in a distributed way. Spark shares the RDD with the initial data and, by applying step 1, will provide in step 2 a "virtual" intermediate RDD representing the result of step 1 without necessarily immediately rotating the calculation. When the result of step 2 is requested, Spark will combine the calculations required in steps 1 and 2 into one Spark job that will: 1. Read the initial data 2. Perform steps 1 and 2, the intermediate result remaining in memory. 3. Save the result in a distributed way. Spark thus avoids expensive distributed writing and replay and then only requires the execution of one job (each job having an incompressible structure cost). When the algorithm has several steps, the time saving becomes considerable! Two types of operations (In technical terms, Spark calculates a direct acyclic graph of the operations to be performed, like Apache Storm or Apache Tez) can be performed on RDDs: transformations and actions. Transformations return a new "virtual" RDD: nothing is then evaluated or persisted, while the actions evaluate and return a value. After an action, all the previous transformations are then computed (see the repository in the compute folder).

6. IMPLEMENTATION

We have used the following technologies for many reasons. Hadoop assumes that conventional approaches (consisting of developing ever more powerful centralized systems) have technical and financial limitations. The development of distributed systems consisting of machines or nodes, relatively affordable (commodity hardware) and scaling out is an alternative from a technical and financial point of view because a distributed system comprising tens, hundreds or thousands of nodes will regularly be confronted with hardware and/or software failures. Google has developed the Google File System (GFS), ancestor of the Hadoop Disrelated File System (HDFS) [Alexandros Baltas and Andreas Kanavos and Athanasios K. Tsakalidis 2017] and The MapReduce Approach. A Hadoop program usually implements both map tasks and reduce tasks. Hadoop is particularly effective for dealing with problems that have one or more of the following characteristics: Volume of data to store or process very important. Need to perform processing on all data (batch rather than transactional, therefore). Heterogeneous data in terms of origin, structure, and format (JSON for example, Tweets collected via any Tweeter API are send in JSON because of the flexibility of this type of object. Several examples are in the repository for interested readers). Execute the tasks of a Hadoop job in parallel, without a pre-established order. A Hadoop cluster is made up of tens, hundreds, or thousands of nodes. It is the addition of the storage and processing capacities of each of these nodes which makes it possible to offer a storage space and a computing power yet to handle data volumes of several To or Po. To improve the performance of a read / write cluster, Hadoops file management system, HDFS, writes and reads files in blocks of 64 MB or 128 MB. Working on such large blocks maximizes data transfer rates by limiting search time on hard drives (seek time). MapReduce is a programming model designed specifically to read, process and write very large volumes of data. A Hadoop program usually implements both map tasks and reduce tasks those programs are usually divided into three parts: The driver, which runs on a client machine, is responsible for configuring the job and submitting it for execution. The map is responsible for reading and processing data stored on disk. The reducer is responsible for consolidating the results from the map and write them on disk. Naturally, the implementation core use Hadoop for these reasons.

7. WEB APPLICATION

7.1 Conception of the DataBase (Web Site)

In order to allow quick access to the data on the website at any time, we had to make a lot of pre-payment. Finally, by budget limitation, we can not offer a database with a very strong capacity of cpu or datawharehouse we can manage peta byte data. The PostgresSQL database is based on a micro instance of 1 CPU and 2 GB of ram. With this configuration, it is clearly impossible to perform complicated SQL queries such as group by, cost, and other aggregation on 350 million lines. For this reason, we decided to optimize our database and create a table corresponding to a data item that we want to display. The query is thus done only on indexes, the response time is then very fast (100ms maximum) regardless of the size of the table. To do this, we had to proceed by step: 1st step: The first step was to define exactly the data we wanted to display: We selected temporal data (Psychological evolution during the year, for each month, according to the time), as well as trends, better users and best retweets monthly / yearly. We also chose to be able to display the psychological profile for each user (Global psychological evaluation, number of tweet / retweet and evolution over the year). 2nd step: We coded Spark scripts for each problem to calculate what we wanted to display. All calculation scripts are here[4]. 3rd step: Each Spark script returned us an aggregated file as we wanted, we just had to import these files into the corresponding tables taking care to organize our indexes. For example: to retrieve the psychological evolution of a user, we just have to make a simple SQL query on the table *user_stat* with a selection on index (where id = 1656561) and the query we reference in 100ms 12 rows corresponding to each month. The same request with several accreditation operators on the initial table took several minutes to answer us.

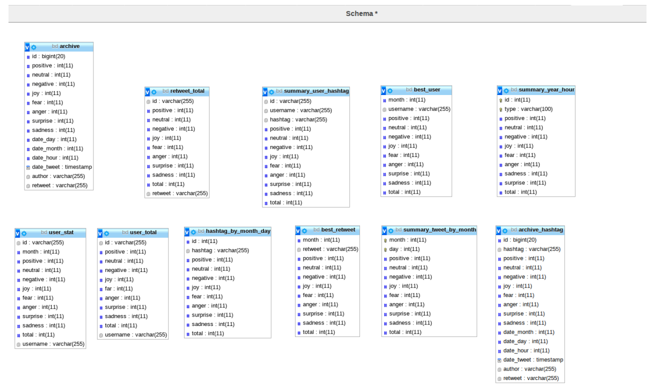

Fig. 4. Schema of the DataBase.

7.2 Conception of the Archive Access

Once the database was created, we wanted the render very easily accessible to the public and we have developed a web platform. The platform presents a very classic web architecture. Our database Postgres with aggreger data is hosted by AWS RDS. We have developed Api RestFul through AWS Lambda and AWS GateWey that are responsible for executing sql requests and returning formatting data. And finally our web client react.js whose sole role is to call the Api Restfull and display the data visualization.

7.3 Conception of the Real Stream

For the real-time part, we chose to use kinesis Data Streams, which is the real-time data analysis service of AWS. For this we have created a Twitter streamer that is responsible for recovering real-time data via the API Stream of twitter. This data is sent to Kinesis Data Streams which allows you to aggregate data from multiple sources. These data are thus sent to a consumer who is responsible for analyzing and predicting the emotion and feeling in real time through textblod and our model of emotion prediction. Once the data is analyzed, our Consumer formats them and sends the result to our web client thanks to MQTT. Real streams scripts can be found here[5]. The streamTwitter.py file is our Twitter streamer and the kinesisStream.py file is our Consumer.

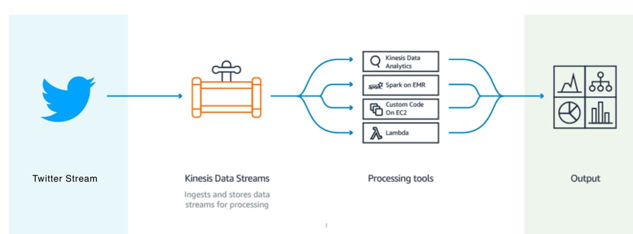

Fig. 5. Schema for the Real Stream Web Application.

[4] https://github.com/yannistannier/twitter-sentiment-analysis/tree/master/compute

[5] https://github.com/yannistannier/twitter-sentiment-analysis/tree/master/kinesis-realtime

8. RESULTS

8.1 Classification - F-Measure

Table III. Binary Classification Results

Classifier	Best Solution Publication	Our Solution
NaivesBayes	0.728	0.772
LogisticRegression	0.665	0.78
DecisionTrees	0.597	0.68
RandomForest	-	0.72
LinearSVM	-	0.80
SGBClassifier	-	0.74

Table IV. Ternary Classification Results From Publication

Classifier	Positive	Negative	Neutral	Total
NaivesBayes	0.717	0.75	0.617	0.696
LogisticRegression	0.628	0.592	0.542	0.591
DecisionTrees	0.646	0.727	0.557	0.643

Table V. Our Results For Ternary Classification Results

Classifier	Positive	Negative	Neutral	Total
NaivesBayes	0.54	0.72	0.60	0.63
LogisticRegression	0.62	0.74	0.64	0.67
DecisionTrees	0.58	0.68	0.59	0.62
RandomForest	0.58	0.72	0.62	0.65
LinearSVM	0.61	0.72	0.62	0.66
SGBClassifier	0.60	0.74	0.62	0.66

As we early introduced in related work, we can say that in the case of the binary classification, our method of preprocessing the data gives better results than that of the publication. We can also see that the SVM allows us to have the best accuracy. However, in the case of ternary classification, the method of publication is superior.

8.2 English tweets monthly analyzed

We analyzed the set of English tweets on the year, dividing by month to see any evolution or regression during the year. A thorough American sociological study on the year 2017 could give the reasons for the graph. We were surprised at the symmetry between joy and sadness, proof that the emotional analysis is not as biased as one might think.

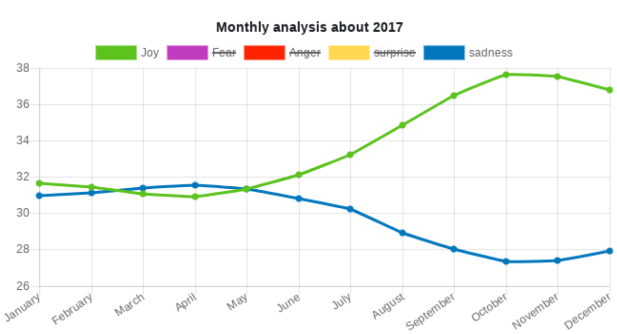

Fig. 6. Results by month for joy and sadness emotions during the 2017.

8.3 Psychological profile for any users

We have implemented a psychological profile by current user in the database (note that this feature and also available in the case of streaming too).Structure similarity context are a also in search [Xiaomei et al. 2018].The problem of sentiment analysis from archive tweets is that there are not so many tweets as one does not imagine per user. We implemented a solution in the website[6].

8.4 Impacts of tweets

In this section, we wanted to talk about the effect of tweets on the community, taking the utmost retweeting the tweet of Donals Trump. We have 414 716 retweet which allows to have a number of acceptable messages to use the word ”impacts”. In this publication, [Vyasa and V.Umab 2017], we found interisting their fought on what they call ”influence” and tools used about that. It is interesting in the field of politics but also in the media world to have an analysis of what is said and done in the world today.

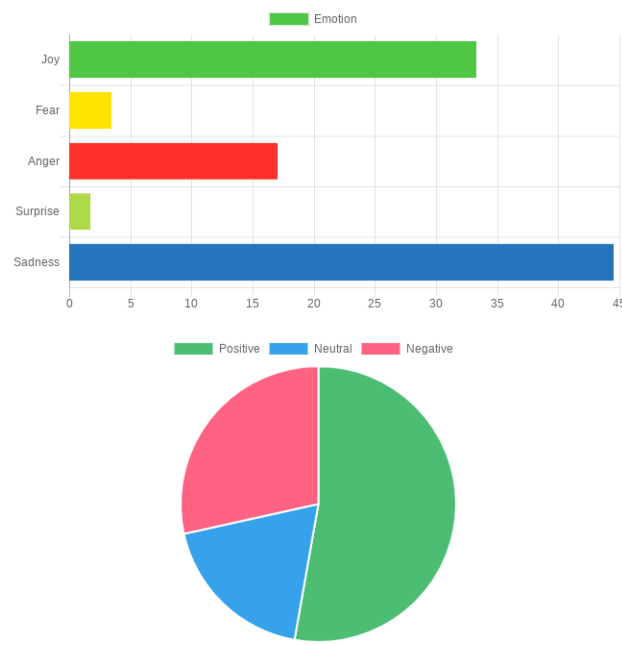

Fig. 7. Results for the emotions ratio on the 414 716 retweeted Donald Trump tweets computed.

8.5 English tweets monthly analyzed

We analyzed the set of English tweets on the year, dividing by month to see any evolution or regression during the year. A thorough American sociological study on the year 2017 could give the reasons for the graph. We were surprised at the symmetry between joy and sadness, proof that the emotional analysis is not as biased as one might think.

[6] https://twitter.yannistannier.io/#/archive/user

8.6 Comparaison of TextBloB and True Results for Emotion Relation

Nous allons discuter maintenant de la cohrance de rsultats.

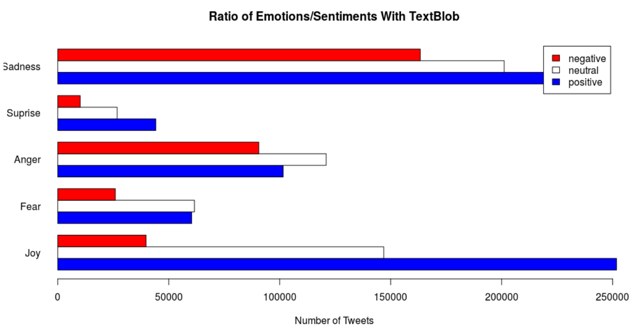

Fig. 8. Results for ratio Emotion/Sentiment with Number of tweets using TextBlob

In this paragraph we will start with TextBlob, the famous sentiment analyzer in the world of open source. The problem here is that the library offers 3 variables for the feeling. We can see that tweets are considered either negative, positive, or neutral gold in the basic data set we only have 2 possible values (positive or negative). Here there is a contradiction of analysis, the sad messages are mostly positive. The explanation here is that a number of tweet considered neutral should be either positive or negative, the introduction of this new posibility of values makes the model over-learning for feelings. Below is a summary table with the exact values.

Table VI. Cross Tab between sentiments and emotions using TextBloB

S\E	Joy	Fear	Anger	Surprise	Sadness
Positive	251 787	60 325	101 556	441 75	233 604
Neutral	146 876	61 592	120 944	26 772	201154
Negative	39 802	25 950	90 601	10 131	163 358

We do not have emotions variables in order to have an overview of our model of emotions to train from an SVM but as this graph indicates, there is a coherence in our results. Sad messages are considered negative and happy messages are positive. For the other cases, it would be necessary to realize a psychological study between feeling and emotions deepened in oneself.

Table VII. Cross Tab between sentiments and emotions using True Labels

S\E	Joy	Fear	Anger	Surprise	Sadness
Positive	312 055	74 474	133 921	51 094	218 641
Negative	126 410	73 393	179 180	29 984	379 475

Above the results obtained for the list of tweets that are 1,578,627 in the sample.

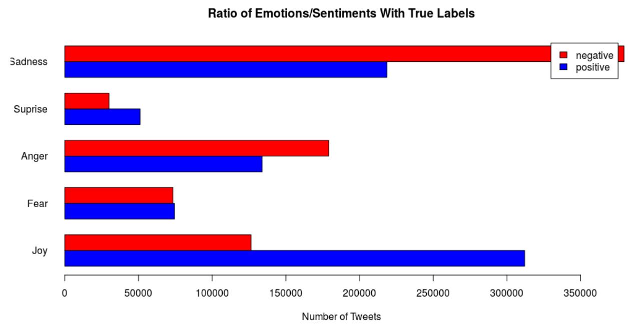

Fig. 9. Results for ratio Emotion/Sentiment with Number of tweets using True Labels

9. DISCUSSION

We now turn our attention to the following interesting question: whether the subjective data that exist on the web carry useful information. Information can be thought of as data that reduce our uncertainty about some subject.This is an example with a sample of 383 623 424 tweets in English.

Table VIII. Cross Tab between sentiments and emotions

S\E	Joy	Fear	Anger	Surprise	Sadness
Positive	63 559 579	9 296 846	27 861 247	7 768 707	42 382 993
Neutral	55 127 659	15 777 833	42 460 015	8 879 626	48 232 835
Negative	9 054 496	3 395 622	23 281 712	1 948 578	24 595 676

According to this view, the diversity and pluralism of information on different topics can have a rather negative role. It is well understood, that true knowledge is being described by facts, rather than subjective opinions [Thakkar and Patel 2015]. However, this diversity in opinions, when analyzed, may deliver new information and contribute to the overall knowledge of a subject matter. This is especially true when the object of our study is the attitude of people. In this case, opinion native data can be useful to uncover the distribution of sentiments across time, or different groups of people. However, data mining differs from machine learning and statistics in that it deals with large volumes of data, stored primarily on disk. Some types of knowledge discovered from a database can be represented by a set of rules. The following is an example of a rule, stated informally: Donald Trump and his totals of retweets incomes are greater than the average with the most sadly effects on users. Of course, such riles are not universally true, and have degrees of support and confidence. Other types of knowledge are represented by equations relating different variables to each other, or by other mechanisms for predicting outcomes when the values of some variables are known. There are a variety of possible types of patterns that may be useful, and different techniques are used to find different types of patterns. Usually there is a manual component to data mining, consisting of preprocessing data to a form acceptable to the algorithms and post-processing of discovered patterns. For this reason, data mining is really a semiautomatic process in real life. The mode widely used applications are those that requires some sort of prediction. In our case, we want to predict emotions and sentiments, then a psychological profile. We outline what is classification, study techniques for building one type of classifiers, called decision-tree classifiers, and then study other predication techniques. Abstractly, the classification problem is this: Given that user in the archive, and given his tweet. We use a given instances of items along with the classes to which they belong, the problem is to predict the class. Since we associate several classes together, then we come to conflicting analyzes.

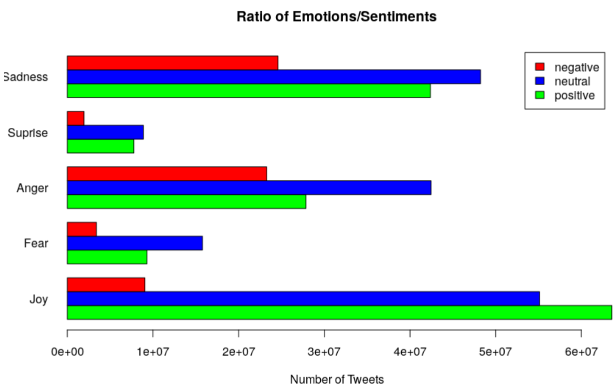

Fig. 10. Results for ratio Emotion/Sentiment with Number of tweets

First non-surprising results like Joy/Positive at 49.75 % and Joy/Negative at 7.08 %. We can see that we normally associate sadness with something negative, for example, but here we see that positive feelings are predominant, just as anger has a majority of positive feelings. One publication can also be referred [Alm et al. 2005] because accordly to this addition between emotion and sentiment, they also have other results.

10. CONCLUSION AND FUTURE WORK

In this report we have presented a sentiment analysis tool on a Web interface, in one hand we used data from an archive end in the other we used real time stream analysis. Due to the absence of labelled data we couldn't argue on reliability of data. This recent publication really question us about the limit on software engineering [Bin Lin and Fiorella Zampetti and Gabriele Bavota and Massimiliano Di Penta and Michele Lanza, and Rocco Oliveto 2018], but they did not explored deep learning [Hardik Meisheri and Rupsa Saha and Priyanka Sinha and Lipika Dey 2017] and what we could achieve with this learning techniques using neural network fully connected that we always only get better with time because of optimized function behind and great computation that we have nowadays due to GPU to build deep learning classifier [Araque et al. 2017]. There are also other features for the real stream [7] such as geolocation of people, we could then generate a graph as a center to any user and know its impact on an interactive map, this would allow among other things to know the influence for example.

11. REFERENCES

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[7] https://twitter.yannistannier.io/#/realtime

REFERENCES

German Rigau Aitor García-Pablos, Montse Cuadros. 2017. W2VLDA: Almost unsupervised system for Aspect Based Sentiment Analysis. *Expert Systems With Applications* 91 (Sept. 2017), 127–137. http://dx.doi.org/10.1016/j.eswa.2017.08.049

Alexandros Baltas and Andreas Kanavos and Athanasios K. Tsakalidis. 2017. An Apache Spark Implementation for Sentiment Analysis on Twitter Data. (Aug. 2017), 15–25. DOI:http://dx.doi.org/10.1007/978-3-319-57045-7_2

Cecilia Ovesdotter Alm, Dan Roth, and Richard Sproat. 2005. Emotions from text machine learning for text-based emotion prediction. (10 2005), 579–586.

Agarwal Apoorv, Boyi Xie, Ilia Vovsha, Owen Rambow, and Rebecca Passonneau. 2011. Sentiment Analysis of Twitter Data. (2011), 30–38. http://dl.acm.org/citation.cfm?id=2021109.2021114

Oscar Araque, Ignacio Corcuera-Platas, J. Fernando Snchez-Rada, and Carlos A. Iglesias. 2017. Enhancing deep learning sentiment analysis with ensemble techniques in social applications. *Expert Systems with Applications* 77 (2017), 236 – 246. DOI:http://dx.doi.org/https://doi.org/10.1016/j.eswa.2017.02.002

Bin Lin and Fiorella Zampetti and Gabriele Bavota and Massimiliano Di Penta and Michele Lanza, and Rocco Oliveto. 2018. Sentiment Analysis for Software Engineering: How Far Can We Go ? (2018), 1–11.

Felipe Bravo-Marquez and Eibe Frank and Saif M. Mohammad and Bernhard Pfahringer. 2016. Determining WordEmotion Associations from Tweets by Multi-Label Classification. (oct 2016), 536–539.

Yogesh Garg and Niladri Chatterjee. 2014. Sentiment Analysis of Twitter Feeds. (2014), 33–52.

Bhumika Gupta, Monika Negi, Kanika Vishwakarma, Goldi Rawat, and Priyanka Badhani. 2017. Study of Twitter Sentiment Analysis using Machine Learning Algorithms on Python. *International Journal of Computer Applications* 165, 9 (May 2017), 29–34. DOI:http://dx.doi.org/10.5120/ijca2017914022

Hardik Meisheri and Rupsa Saha and Priyanka Sinha and Lipika Dey. 2017. A Deep Learning Approach to Sentiment Intensity Scoring of English Tweets. *Proceedings of the 8th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis* 8, 7 (Sept. 2017), 193–199. DOI:http://dx.doi.org/10.1038/s41598-018-20132-7

Saif Hassan, He Yulan, and Alani Harith. 2012. Semantic Sentiment Analysis of Twitter. (2012), 508–524.

Nazan Öztürka and Serkan Ayvazb. 2017. Sentiment analysis on Twitter: A text mining approach to the Syrian refugee crisis. *Telematics and Informatics* 35 (Oct. 2017), 136–147. DOI:http://dx.doi.org/10.1016/j.procs.2017.12.044

Lahari Poddar, Kishaloy Halder, and Xianyan Jia. 2016. Sentiment Analysis for Twitter : Going Beyond Tweet Text. *CoRR* abs/1611.09441 (2016).

Harsh Thakkar and Dhiren R. Patel. 2015. Approaches for Sentiment Analysis on Twitter: A State-of-Art study. *CoRR* abs/1512.01043 (2015). http://arxiv.org/abs/1512.01043

Themis Palpanas and Mikalai Tsytsarau. 2011. Survey on mining subjective data on the web. *Expert Systems With Applications* 24 (Oct. 2011), 478–514. DOI:http://dx.doi.org/10.1007/s10618-011-0238-6

Vishal Vyasa and V.Umab. 2017. An Extensive study of Sentiment Analysis tools and Binary. *Procedia Computer Science* 125 (Dec. 2017), 193–199. DOI:http://dx.doi.org/10.1016/j.procs.2017.12.044

Walaa Medhat and Ahmed Hassan and Hoda Korashy. 2014. Sentiment analysis algorithms and applications: A survey. *Ain Shams Engineering Journal* 5, 4 (2014), 1093–1113. DOI:http://dx.doi.org/{10.1016/j.asej.2014.04.011}

Zou Xiaomei, Yang Jing, and Zhang Jianpei. 2018. Microblog sentiment analysis using social and topic context. *PLOS ONE* 13, 2 (02 2018), 1–24. DOI:http://dx.doi.org/10.1371/journal.pone.0191163

Zhao Jianqiang and Gui Xiaolin. 2017. Comparison Research on Text Pre-processing Methods on Twitter Sentiment Analysis. *IEEE Access* 5 (Feb. 2017), 2870–2879. DOI:http://dx.doi.org/10.1109/ACCESS.2017.2672677