Social Media, Marketing and Business Intelligence
Stratebi. Open Business Intelligence
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SOCIAL MEDIA DATA

Nowadays thanks to technology, corporations are overwhelmed by large data volumes representing business processes and its environment. By virtue of powerful BI tools such as Pentaho Business Analytics, we will be able to transform raw data into information, and information into knowledge. It is not enough to own data and indicators stored in a database, but also we need to know how to take advantage of them in order to improve decision making process and being more competitive.

The increasing use of technology and the appearance of Web 2.0 and Social Networks has changed the way users surf on the internet. Rather than being merely an audience, users increasingly interact with each other. Currently, they tend to share personal content: reviews, photos, videos... and as a consequence every day a very large volume of data that is not being analyzed now. If we collect and process social media data we could be able to build business indicators which could help in increasing an organization’s profits.

Today there are millions of blogs dealing with different themes, a wide variety of social networks, mass media. Maybe Facebook and Twitter are the most well known but there are many more: Flicker, LinkedIn, MySpace, Google+, Xing ... and all are sources of valuable information.

THE BENEFITS OF ANALYZING SOCIAL MEDIA DATA

Analyzing Social Media data gathered together from the sources previously commented any corporation can achieve short-term profits:

**Marketing Optimization.** Today’s tools are not valid to know in which population sectors focus our campaigns; however with social media techniques these capabilities will be acquired.

For example, after publishing a photo of a new product we could count the number of likes and get valuable information about the users you have attracted with a promotion, this information will be very useful for oriented advertising campaigns.

**Capture ideas and dissatisfied clients.** We will identify client’s needs and wishes about our products, thanks to this fact we will discover the deficiencies of our articles and services.

**Situational awareness.** Using social media data lets us control market trends and understanding the causes of complaints, armed with these knowledge executive stakeholders will take every action possible to protect their brands.

Analyzing comments on Facebook or Twitter we can gain new ideas and discover the issues that clients have experienced. Furthermore, by means of this process we will be able to detect future trends and we could be distinctive in our market.
Sentiment analysis. “What does the world think about us?” or “What does the world think about our new product?” are only two examples of questions that have no answer without analyzing social media data. Picking Twitter as example, if a marketing promotion spreads around the world, several thousands of tweets should be processed by Text Mining techniques. These methods allow us to extract sentiments from tweet entities useful to comprehend the opinions of our organizations and acquiring knowledge.

These days, most entertainment companies monitor the opinions about its TV series, saving a lot of money removing from the schedule the ones not financially feasible.

MARKETING CAMPAIGNS ANALYSIS

Every company today has a tool for managing customer relationships (customer relationship management, CRM) with a CRM tool you can find, attract, gain and maintain customers using powerful marketing plans. These tasks shall be accomplished through marketing strategies using a wide variety of advertising channels: email marketing, search engine marketing, affiliate marketing, display advertising, social networking, social media, and many others.

From Stratebi, we will help you take maximum advantage of these channels with a common goal: optimizing your advertising campaigns to achieve a higher return on investment.

MARKETING CAMPAIGN ANALYSIS CASE STUDY

Suppose we need to promote an event with all its information contained in a website, our strategy will be advertising the meeting looking for getting more knowledge about the event. Three channels will be used for this task and website’s URL is the link between them:

- Mail Marketing: An email will be sent to every person in our CRM. At an early stage this action will not be directed to a specific sort of contact and only general information will be included in the message.
- Twitter: A set of informational tweets will be published mentioning the event’s URL.
- Facebook: A collection of comments about the event will be published in the company account timeline.

After carrying out the advertising campaign on the different channels, we will collect all data extracted from the different sources with the purpose of examining promotion results. Later with the knowledge acquired in the first stage of the campaign new enhanced promotions can be taken:

- Mail Marketing: statistics regarding email Opens, Clicks, Soft & Hard Bounces, Unsubscribes and Forwards are obtained.
• Twitter: statistics regarding retweets, followers, favorites, sentiment of a reply (i.e. :-) good feeling, :-( bad feeling) ... are collected through this case of study.
• Facebook: Statistics such as likes, comments, and shares of each advertising post, as well as how much negative feedback each post has received can be seen.

Putting all available data together the campaign will allow us to analyze the results in-depth. Besides, the analysis of this information in a unique tool is made possible. Traditionally the results were analyzed separately for each channel.

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**IMPROVING YOUR ENTERPRISE MARKETING MANAGEMENT**

As seen in the previous example, any company joining data from different advertising channels (Mail Marketing, digital media and social networks) will achieve the ability to modify an in process campaign without waiting for final results.

These days, enterprises launch ad campaigns by means of their marketing department. These corporative departments follow a work schedule and no feedback is returned from the promotions until the end of them. For example, if we launch a promotion for a training boot camp and its registration period extends during one month; marketing executives will only have visibility of the results at the end of the period.

From Stratebi, we intend to provide valuable analytics tools to these departments in order to guarantee a daily evolution monitoring; using this Business Intelligence systems, campaign managers could make decisions fed by real-time data. This improvement in the efficiency of the advertising process will impact increasing sales volume. For example, if during the first week the highest percentage of sales was produced by people between 20 and 27 years maybe focusing the campaign in youth sector could be an exceptional idea to boost sales. Furthermore, if you are provided with real-time information you will get an advantage over your market competitors.
HOW AND WHAT TO ANALYZE

How can I set up KPIs (key performance indicators) for social media data? So, in terms of analytics we could track the following:

- Traffic data: How many visitors did social media drive to your site?
- Fans and follower data: How many people are in your networks and how are they developing?
- Social content performance: How is the content that you produce performing on social sites?
- Social Interaction data: How are people interacting and sharing your content on the networks?

Nowadays, there are many online tools to measure your presence on social networks; however they are limited since some of them don’t include custom KPIs and others are hosted in cloud servers not optimized for massive analysis.

For these reasons, Stratebi offers its wide experience in the Open Source Business Intelligence field (Pentaho Suite tool) and encourages you to contact us to create a project which collects all data available, in this case social media data and take the best of the information by designing custom KPIs and creating dashboards, reports and analysis views. Building tailor-made solutions we will be able to analyze the data from client’s perspective preventing users from others tools restrictions.

Image: Social media data analysis process

SOCIAL MEDIA KPIS

Performance indicators (KPIs) help an organization define and measure progress toward organizational goals. Nowadays there are many social networks but in this document we are focusing on KPIs of the most important: Facebook and Twitter.

Facebook.

Facebook is the world’s largest social network, with over 850 million monthly active users. This social network is valuable as a source of information if used properly.

As everybody knows Facebook contains the following elements to be analyzed:
- **Resources.** Photos, videos, statuses, questions, links... are the entities users will interact with. These resources have common informations: likes, comments and shares.

- **People.** Facebook collects two types of information: personal details provided by a user and usage data collected automatically as the user spends time on the Web site clicking around. Regarding personal information, the user willfully discloses it, such as name, email address, telephone number, address, gender and religious views for example. Facebook now has fine-grained privacy settings for its users. Users can decide which part of their information should be visible and to whom, however, by default all the information available in a user profile is public and as a consequence when studying a campaign with a large sample size the results produced will be accurate.

**Image:** Photo.
**Image:** User profile. Mark Zuckerberg Facebook’s founder

**Image:** Basic Info

- **Fecha de nacimiento:** 14 de mayo de 1984
- **Sexo:** Hombre
- **Idiomas:** Idioma inglés y Chino mandarín
Therefore, taking into account the previous Facebook resources, the first step is to define KPIs and measure against them. There are several indicators to track:

- Number of shares
- Resources with higher interaction rates
- Number of likes
- Number of comments
- Geolocation

**Twitter.**

Twitter is an online social networking and microblogging service that enables users to publish and read text-based messages up to 140 characters, known as "tweets". Over 350 millions tweets are generated daily and a not inconsiderable number of them are related to your business or industry, don’t underestimate this knowledge.

Twitter contains the following items to be analyzed:

- “Tweets”. A tweet is a post or status update on this social network; they are little pieces of information containing news, conversations, opinions...

- People. Twitter’s users are content creators since they are responsible for posting messages. Besides, each user has a profile including name, location, website, biography and this helpful information will be very interesting to be analysed.
• Hashtag. The # symbol, called a hashtag, is used to mark keywords or topics in a Tweet. It was created organically by Twitter users as a way to categorize messages. This mark will increase efficiency when searching for opinions.

Image: Twitter user profile page.

Image: Information contained on an individual tweet
Even though we don’t have much information a priori, nevertheless with the right twitter KPIs and metrics, you can effectively monitor campaigns to ensure you get the best financial outcomes:

- Number of retweets
- Number of favorites
- Number of mentions
- Total number of followers
- Number of replies
- Ratio following vs followers
- Number of lists I belong to
ETL PROCESSES FOR SOCIAL DATA

ETL is the process of extracting data, mostly from different types of systems, transforming it into a structure that's more appropriate for reporting and analysis and finally loading it into the datawarehouse.

On a Social Data analysis large amounts of data will be assessed, i.e. for a simple facebook post which includes date, location, text content... the amount of likes, shares and all the reply comments about it must be taken into account. Besides, each individual interaction includes a facebook user with its corresponding profile, owing to these vasts amounts of data the creation of a Business Intelligence project appears necessary to support better business decision-making.

HOW TO EXTRACT DATA

Most popular social networks include resources to extract information from them. The main tool is the API (Application Programming Interface) which allows a technical user to retrieve data in multiple formats (XML, JSON).

FACEBOOK API

As an example we are going to discover Facebook’s API. In the image below Facebook console is displayed, using this tool we will be able to perform API calls and gathering data. In this case we are searching for Spanish national football team facebook page (search term “La Selección Española”). As can be seen, console returns basic information: likes, location, category, website...

Image: Facebook’s API screencapture
Suppose we want to get the information associated with links published in this Facebook page since it looks like important for us to find out how is fans response about its content. In this phase we will be helped by Pentaho Data Integration to extract data. Below is showed the image of the extraction and filtering information process. In a first stage a JSON entity is read and in the end we return filtered results.

![Diagram: Fanpage’s links extraction stages](image)

**Image:** Fanpage’s links extraction stages

The following screencapture shows the results obtained, as can be observed the information retrieved (likes, comments, creation date, URL) corresponds to last 10 TimeLine publications from “La Selección Española de Fútbol” page and particularly link type posts.

<table>
<thead>
<tr>
<th>link</th>
<th>59</th>
<th>0</th>
<th>La Vuelt a España</th>
<th>2012-08-17T08:58:34+0000</th>
</tr>
</thead>
<tbody>
<tr>
<td>link</td>
<td>20</td>
<td>0</td>
<td>Levante • El polo de Daiaz Dosba jugaba en el levante</td>
<td>2012-08-17T08:39+0000</td>
</tr>
<tr>
<td>link</td>
<td>14</td>
<td>0</td>
<td>Espanyol • Simoa Saboneu ficha por el Espanyol</td>
<td>2012-08-17T08:39+0000</td>
</tr>
<tr>
<td>link</td>
<td>15</td>
<td>0</td>
<td>Queens Park Rangers • Rongeza firma con el QPR</td>
<td>2012-08-17T08:39+0000</td>
</tr>
<tr>
<td>link</td>
<td>11</td>
<td>0</td>
<td>Fútbol en Portugal • Liiga Sagres 2012 / 2013</td>
<td>2012-08-17T08:39+0000</td>
</tr>
<tr>
<td>link</td>
<td>20</td>
<td>0</td>
<td>Liverpool • Oussama Assaidi, tercer fichaje del Liverpool</td>
<td>2012-08-17T08:39+0000</td>
</tr>
<tr>
<td>link</td>
<td>15</td>
<td>0</td>
<td>2ª División A • Liga Adelante 2012 / 2013 (Post General)</td>
<td>2012-08-17T08:39+0000</td>
</tr>
<tr>
<td>link</td>
<td>26</td>
<td>0</td>
<td>Primera División • Liga BBVA 2012 / 2013 (Post general)</td>
<td>2012-08-17T08:39+0000</td>
</tr>
<tr>
<td>link</td>
<td>26</td>
<td>0</td>
<td>Primera División • Liga BBVA 2012 / 2013 (Post general)</td>
<td>2012-08-17T08:39+0000</td>
</tr>
<tr>
<td>link</td>
<td>9</td>
<td>0</td>
<td>Fútbol Base Madrid • SOLEDAD DE ACCESO CATEGORÍAS BASE REAL C.D. CARABANCHEL</td>
<td>2012-08-17T08:39+0000</td>
</tr>
</tbody>
</table>

**Image:** ETL results

Finally, as could be appreciated from the previous example it is quite easy to extract information from Facebook with the support of Pentaho Data Integration. The main steps in obtaining information from Facebook's API is to have very clear the data we are looking for and of course understanding API tricks.
SOCIAL MEDIA DASHBOARDS - EXAMPLES

Below a set of examples created with Pentaho suite are exposed. Dashboards have been designed by STDashboard component a proprietary development of Stratebi.

Image: Pentaho login screenshot

Imagen: Pentaho user console screenshot
Next image shows basic twitter data throughout time; this is a global analysis and shows evolution of retweets, mentions, favourites... over time.

**Image:** Twitter account evolution analysis dashboard

The following dashboard analyzes tweets published by an individual account. Retweets and replies are represented in a time zone distribution (AM/PM); in addition to these charts a table summary containing individual tweet stats (comments, mentions and retweets) is displayed. Moreover a barchart with weekday as category and retweets, mentions and comments as series is included.

**Image:** Tweets analysis dashboard
The image below shows the evolution over time of the new members grouped by sex of a Facebook fan page. Besides, a world map with values displayed as a color scale is included. This geographical chart allows drilldown on a certain country to reveal more detailed information.

**Image:** Facebook’s fanpage evolution dashboard

Lastly, a global summary of fans in a Facebook page is showed. Location, Sex, Relationship status, Education and Age stats are analysed in this dashboard.

**Image:** Facebook’s fanpage analysis dashboard
Sentiment Analysis of Twitter Data

Sentiment Analysis, considered one of the most efficient ways to measure social media’s impact helps us to understand our brand impact across social networks. The following case study examines Twitter search engine using the terms “Pentaho” and “Firefox”, however the same methodology can be applied to any other brand or product name.

The technique applied is known as Sentiment Analysis (also known as Opinion Mining, Sentiment Classification or Affective Computing) consists of extracting and classifying subjective information (opinions, ideas...) in source materials (tweets in our case). This procedure uses natural language processing principles since it is the language spoken by people and as a consequence problems arising from ambiguity appear. The challenge of discovering real features of a given search term is the keystone of this tool.

The information monitored by this tool will be beneficial for the marketing department of a company. This procedure could be carried out to analyze commercial brands (i.e. Coca-Cola, Oracle, Ford...), movie premieres and video games releases. Additionally, this technique can be adopted to analyze the tweets for positive or negative sentiment around election candidates.

CASE STUDY

In this case study we start searching on twitter engine the term “pentaho”. We have choosen this term as recently this open source business intelligence based corporation released a new product. In the following screenshot we could observe the process of collecting the source data. A RSS Input step searching tweets including “pentaho” (Pentaho Data Integration 4.3.0) is employed to obtain data.

Image: Tweet extraction stage PDI screenshot (General Tab)
In the Fields tab we will get automatically the fields (Title, Link, Description, Identifier, Publication Date...) retrieved in our search.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{tweet_extraction_stage_pdi_screenshot_fields_tab.png}
\caption{Tweet extraction stage PDI screenshot (Fields Tab)}
\end{figure}

Once we have a great number of tweets processed with the help of Pentaho Data Integration tool (aka Kettle) it is the moment to construct a Tag Cloud having as source the text of all tweets. This is a first approach to find related words and expressions. At first glance a person with no knowledge of pentaho term can gain an insight into it. We should remark the fact that pentaho word is excluded in this word cloud since it is the connector between all entities.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{pentaho_tag_cloud.png}
\caption{Pentaho tag cloud.}
\end{figure}
Now, we continue considering hashtags included in our sample. Analyzing twitter’s hashtags will reveal categories to us. Hashtagging you can remark a particular theme, expressing an opinion or even a personal feeling (examples: #PentahoWebinar, #IlovePentaho, #BusinessIntelligence, #PeopleIWantToMeet).

Imagen: Hashtag word cloud.

In the screenshot we could check that “pentaho” is obviously the main hashtag, however “bigdata” and ”Pentaho45” tags are also very common. These hashtags mark the popularity of the latest pentaho suite release and the incorporation of big data capabilities from the aforementioned software. You may be surprised by getting so much information from a simple automatic analysis.

In the third phase of this research we are going to carry out a Data Mining study, nevertheless due to the small sample size (750 tweets) and the nature of them (after human evaluation the great majority express a positive polarity and only 20 tweets express dislike of Pentaho) this study has been aborted. The reason for rejecting this experiment is the lack of negative polarity cases which are essential to guarantee the correct function of the learning stage of data mining algorithms.

As an alternative, we are using “Firefox” term to perform the research, with this new search over 1500 tweets are gathered about the browser. A subset of 400 tweets have been human evaluated and the rest will be SQL script analyzed looking for words and emoticons expressing sentiments (examples: like, love, nice, cool, great, hate, crash, crazy, fail, error, 😞, 😇). After analyzing all tweets we need to create 2 ARFF (Atribute-Relation File Format) files which will feed Weka Data Mining tool:

- Firefox_total_tweets_set.arff (1500 tweets)
- Firefox_training_set.arff (400 tweets)

The training set will be destined to train the algorithms in our study.
K-means is a greedy clustering method which aims to partition a set of observations into k clusters in which each observation belongs to the cluster with the nearest mean. In our study case we will use the Euclidean distance calculated from each point to the cluster center, this distance will be useful for the grouping stage of the algorithm. K-means algorithm will be very helpful for us as first approach since it is a fast and efficient algorithm. Due to the properties of the source data, we have chosen 3 as k value since it appears possible that we could distinguish between positive, negative and neutral tweets.

In this research we are going to take advantage of Weka software since it is included in Pentaho suite. We should initially provide Weka the ARFF file containing the training set (400 tweets). Next in Cluster tab we will choose SimpleKMeans algorithm setting manually the field numClusters with number 3, then we should pick the total tweets set (1500 tweets) as the test set. After configuring the algorithm settings just press start and Weka will execute the following actions:

1) Get training data as master data and effectuate a learning process.

2) Evaluate total tweets set with the knowledge acquired in the previous step, in this phase the algorithm makes a prediction about the cluster that each tweet belongs to. The learning process is named model and can be stored as a .model file, besides this sort of files can be used in Weka and in PDI Weka Scoring step.

Training set (human evaluation):

<table>
<thead>
<tr>
<th>Polarity</th>
<th>No. of tweets</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive</td>
<td>228</td>
</tr>
<tr>
<td>Negative</td>
<td>98</td>
</tr>
<tr>
<td>Neutral</td>
<td>93</td>
</tr>
<tr>
<td>TOTAL</td>
<td>419</td>
</tr>
</tbody>
</table>
The results obtained show that cluster number 0 includes tweets with negative opinions as the average value of the negative attributes (negative and negative_smiley) is the highest. On the other hand, cluster with label 1 stores the set of 228 tweets human evaluated as positive. Finally in cluster number 2 will contain neutral entities.

\[
\text{Table: Cluster centroids}
\]

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Full Data</th>
<th>Cluster 0</th>
<th>Cluster 1</th>
<th>Cluster 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>positive</td>
<td>0.4062</td>
<td>0.2551</td>
<td>1.0044</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>+/-0.4063</td>
<td>+/-0.5974</td>
<td>+/-0.8288</td>
<td>+/-0</td>
</tr>
<tr>
<td>positive_smiley</td>
<td>0.0453</td>
<td>0</td>
<td>0.0633</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>+/-0.2083</td>
<td>+/-0</td>
<td>+/-0.277</td>
<td>+/-0</td>
</tr>
<tr>
<td>negative</td>
<td>0.3031</td>
<td>1.1224</td>
<td>0.0746</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>+/-0.5861</td>
<td>+/-0</td>
<td>+/-0.3694</td>
<td>+/-0</td>
</tr>
<tr>
<td>negative_smiley</td>
<td>0.0143</td>
<td>0.0612</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>+/-0.1189</td>
<td>+/-0</td>
<td>+/-0</td>
<td>+/-0</td>
</tr>
</tbody>
</table>

\[
\text{h_eval: Good Bad Good Neutral}
\]

- Bad: 95 (23%) 98 (100%) 0 (0%) 0 (0%)
- Good: 228 (54%) 0 (0%) 228 (100%) 0 (0%)
- Neutral: 93 (22%) 0 (0%) 0 (0%) 93 (100%)
- Not Classified: 0 (0%) 0 (0%) 0 (0%) 0 (0%)

--- Evaluation on test set ---

Clustered Instances

<table>
<thead>
<tr>
<th>Cluster</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>188 (12%)</td>
</tr>
<tr>
<td>1</td>
<td>395 (25%)</td>
</tr>
<tr>
<td>2</td>
<td>967 (62%)</td>
</tr>
</tbody>
</table>

**Image:** K-means results

K-means algorithm after the learning process, classifies the total tweets set in the following manner: Cluster 0 (188 tweets), Cluster 1 (395 tweets) and Cluster 2 (967 tweets).

Total tweets set (3-means algorithm automatic evaluation):

<table>
<thead>
<tr>
<th>Polarity</th>
<th>No. of tweets</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive</td>
<td>395</td>
</tr>
<tr>
<td>Negative</td>
<td>188</td>
</tr>
<tr>
<td>Neutral</td>
<td>967</td>
</tr>
<tr>
<td>TOTAL</td>
<td>1550</td>
</tr>
</tbody>
</table>
USER CLASSIFIER TREE

In this stage we will manually construct a tree; this created structure is in essence a model. We build the tree using User Classifier as algorithm on Weka. At the start of the process a window containing the total data set will appear in the screen, after clicking on the box a x,y-plane is displayed. Our task is creation of homogeneous groups of tweets.

**Image**: User classifier data visualization

Once finished the initial classification phase, we should change to Tree view section and the following tree model will be shown:

**Image**: User tree visualizer
After closing tree edition window, the algorithm is ready to be executed over the total tweets set, it is important to remember specifying this global set as supplied test set. The following are the results arising from the execution of the algorithm.

#### Confusion Matrix ####

|    | a | b | c | d
|----|---|---|---|---
| a  | 89| 0 | 9 | 0
| b  | 12| 192| 24| 0
| c  | 0 | 0 | 93| 0
| d  | 100| 138| 893| 0

*Image: User tree classification results*

In the screenshot above we could observe the prediction made: 100 negative tweets, 138 positive tweets and 893 neutral ones.

---

**J48 TREE**

J48 is an open source Java implementation of the C 4.5 algorithm in the weka data mining tool. C 4.5 is one of the most popular algorithms in Data Mining. The most important parameter is the pruning confidence level which has direct influence on tree's size and its prediction capabilities.

The confidence level tells us how sure we can be. It is expressed as a percentage and represents how often the true percentage of the population who would pick an answer lies within the confidence interval. C 4.5 default confidence level value is 25%; the lower the confidence level, the more pruning nodes that are pruned. Below we could observe the automatically generated tree (don't forget passing to the algorithm total tweets set as supplied test set).
Image: J48 tree visualizer

J48-tree pseudo-code

```plaintext
negative <= 0
| positive <= 0
| | positive_smiley <= 0
| | | negative_smiley <= 0: Neutral (115.0/22.0)
| | | negative_smiley > 0: Bad (3.0)
| | positive_smiley > 0: Good (8.0)
| positive > 0: Good (190.0)
negative > 0: Bad (103.0/14.0)
```

The following are the results returned by the execution of J48 algorithm:

```
<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>&lt;-- classified as</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>92</td>
<td>0</td>
<td>6</td>
<td>0</td>
<td>a = Bad</td>
</tr>
<tr>
<td>b</td>
<td>14</td>
<td>198</td>
<td>16</td>
<td>0</td>
<td>b = Good</td>
</tr>
<tr>
<td>c</td>
<td>0</td>
<td>93</td>
<td>0</td>
<td>0</td>
<td>c = Neutral</td>
</tr>
<tr>
<td>d</td>
<td>110</td>
<td>147</td>
<td>874</td>
<td>0</td>
<td>d = Not_Classified</td>
</tr>
</tbody>
</table>
```

Image: J48 tree classification results

In the screenshot above we could observe the prediction made by J48 algorithm: 110 negative tweets, 148 positive tweets and 874 neutral ones.
In the table below we could view the performance of these algorithms operating over the same training set. Results obtained (J48 91% good classified vs User tree 89% good classified) show that J48 method is better than User created one as it makes the most accurate prediction.

<table>
<thead>
<tr>
<th>User Tree</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Bad</td>
<td>Good</td>
<td>Neutral</td>
<td>Not_classified</td>
<td>&lt;-Classified as</td>
<td></td>
<td>Good classified:</td>
<td></td>
</tr>
<tr>
<td>89</td>
<td>0</td>
<td>9</td>
<td>0</td>
<td>Bad</td>
<td></td>
<td>374</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>192</td>
<td>24</td>
<td>0</td>
<td>Good</td>
<td></td>
<td>45</td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>93</td>
<td>0</td>
<td>Neutral</td>
<td>% ×</td>
<td>10,74%</td>
<td></td>
</tr>
<tr>
<td>100</td>
<td>138</td>
<td>893</td>
<td>0</td>
<td>Not_Classified</td>
<td>% ✓</td>
<td>89,26%</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>J48</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Bad</td>
<td>Good</td>
<td>Neutral</td>
<td>Not_classified</td>
<td>&lt;-Classified as</td>
<td></td>
<td>Good classified:</td>
<td></td>
</tr>
<tr>
<td>92</td>
<td>0</td>
<td>6</td>
<td>0</td>
<td>Bad</td>
<td></td>
<td>383</td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>198</td>
<td>16</td>
<td>0</td>
<td>Good</td>
<td></td>
<td>36</td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>93</td>
<td>0</td>
<td>Neutral</td>
<td>% ×</td>
<td>8,59%</td>
<td></td>
</tr>
<tr>
<td>110</td>
<td>147</td>
<td>874</td>
<td>0</td>
<td>Not_Classified</td>
<td>% ✓</td>
<td>91,41%</td>
<td></td>
</tr>
</tbody>
</table>

**LINEAR REGRESSION ALGORITHM**

Finally, we will apply linear regression to our case study, this technique consists in modelling the relationship between a scalar dependent variable $Y$, one or more explanatory variables $X_i$ (1≤i≤n) and k constant (equation $Y = a_1X_1 + a_2X_2 + a_3X_3 + ... + a_nX_n + k$).

Before starting the procedural we should normalize variables, on Weka explorer open Preprocess tab and normalize attributes using normalize filter. Now, we have the original values re-scaled to the range [0,1] and thanks to this we will reduce noise caused by high attribute values.

Next, we must open Classify tab and select “Linear Regression” option. In the screenshot below, we could notice the fact that this algorithm includes the option to eliminate collinear attributes (collinear vectors: parallel vectors) so as to create the most accurate line equation.
The equation generated by this linear approach is the following:

\[ h_{\text{eval}} = 0.257 \times \text{positive} + 0.3504 \times \text{positive_smiley} - 1.6282 \times \text{negative} - 1.41 \times \text{negative_smiley} + 0.6314 \]

**ALGORITHM COMPARISON RESULTS**

Lastly, we are going to build a Pentaho Data Integration transformation in order to collect each tweet together with its prediction. The values predicted vary depending on the algorithm employed:

- K-means returns a cluster number.
- User Classifier and J48 trees return the polarity of a tweet.
- Linear Regression returns an integer value contained the following set \{-6, -4, -3, -2, -1, 0, 1\} which measures the sentiment of a tweet, higher values like 1 or 0 are related to positive tweets while values lower than -1 are used to describe tweets containing negative feelings.
Sentiment Analysis of Twitter Data

Finally, a table comparing the algorithms used is shown below. At a glance you can check that the only error in the table belongs to User classifier prediction, since predicts as neutral an unquestionable negative tweet. Besides we can observe how linear regression assigns -3 as value for a tweet that contains several negative terms expressing dissatisfaction and frustration.

<table>
<thead>
<tr>
<th>Tweet</th>
<th>Cluster</th>
<th>User Tree</th>
<th>J48</th>
<th>Linear Regression</th>
</tr>
</thead>
<tbody>
<tr>
<td>Is it just I or is Firefox the browser that hangs and crashes the most? :-(</td>
<td>0 (Bad)</td>
<td>Bad</td>
<td>Bad</td>
<td>-3</td>
</tr>
<tr>
<td>FastestFox - Browse Faster :: Add-ons for Firefox <a href="https://t.co/Khn21Wzo">https://t.co/Khn21Wzo</a></td>
<td>1 (Good)</td>
<td>Good</td>
<td>Good</td>
<td>1</td>
</tr>
<tr>
<td>I cant believe that firefox has a better ftp client than android os has.</td>
<td>1 (Good)</td>
<td>Good</td>
<td>Good</td>
<td>1</td>
</tr>
<tr>
<td>FastestFox - Browse Faster :: Add-ons for Firefox <a href="https://t.co/uWQ0Mx5F">https://t.co/uWQ0Mx5F</a></td>
<td>1 (Good)</td>
<td>Good</td>
<td>Good</td>
<td>1</td>
</tr>
<tr>
<td>@gregsdelnikov nice but its dont work on firefox ...</td>
<td>1 (Good)</td>
<td>Bad</td>
<td>Bad</td>
<td>-1</td>
</tr>
<tr>
<td>@danmasso Closed out Firefox and started over. :((</td>
<td>0 (Bad)</td>
<td>Neutral</td>
<td>Bad</td>
<td>-1</td>
</tr>
<tr>
<td>Honestly Firefox is annoying me now. #memorybloat</td>
<td>0 (Bad)</td>
<td>Bad</td>
<td>Bad</td>
<td>-1</td>
</tr>
<tr>
<td>#noscript is the most annoying #firefox addon</td>
<td>0 (Bad)</td>
<td>Bad</td>
<td>Bad</td>
<td>-1</td>
</tr>
<tr>
<td>RT @Three_Ninjas: Firefox crashes once a day.</td>
<td>0 (Bad)</td>
<td>Bad</td>
<td>Bad</td>
<td>-1</td>
</tr>
<tr>
<td>@misterjaydee thanks for the Firefox &lt;3 ^WR</td>
<td>1 (Good)</td>
<td>Good</td>
<td>Good</td>
<td>1</td>
</tr>
<tr>
<td>I hate the new Mozilla Firefox.</td>
<td>0 (Bad)</td>
<td>Bad</td>
<td>Bad</td>
<td>-1</td>
</tr>
<tr>
<td>Oh.. #Firefox is cool too #JustSaying</td>
<td>1 (Good)</td>
<td>Good</td>
<td>Good</td>
<td>1</td>
</tr>
<tr>
<td>Firefox is getting slower day by day</td>
<td>0 (Bad)</td>
<td>Bad</td>
<td>Bad</td>
<td>-1</td>
</tr>
<tr>
<td>Long story short, thanks @firefox</td>
<td>1 (Good)</td>
<td>Good</td>
<td>Good</td>
<td>1</td>
</tr>
<tr>
<td>@tfaiso firefox and good show</td>
<td>1 (Good)</td>
<td>Good</td>
<td>Good</td>
<td>1</td>
</tr>
<tr>
<td>i hate firefox.</td>
<td>0 (Bad)</td>
<td>Bad</td>
<td>Bad</td>
<td>-1</td>
</tr>
</tbody>
</table>

Image: Tweet extraction job Pentaho Data Integration.

Image: Algorithm comparison table.
CONCLUSIONS

The purpose of this paper is to use Pentaho (ETL, STDashboard, Data Mining) tools for obtaining knowledge hidden on social media data. Besides, we find remarkable that the effective use of the methods applied in this research would be a valuable resource for marketing department staff. This paper aims to improve advertising campaign’s productivity and we strongly recommend you to take the best of the social data available using aforementioned techniques.