

User Generated Content and Engagement Analysis in Social Media case of Algerian Brands

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Abstract

Nowadays, online social media hugely influences individuals' daily lives, companies, institutions, and governments. Analyzing the online social content related to the productivity of any company becomes crucial to manage and supervise its activities and future trends. We investigate the quality of social signals and content related to Algerian products and services to enhance their exploitation and deployment. Our investigation relies on the statistical analysis of social signals and the textual analysis of User-Generated Contents (Posts and Comments). The current work has been done on a sample of more than 50 brands gathering products and services on Facebook with 10K posts and their related comments totaling around 100K.

We measure Users/Brand Engagement Rates (ER) considering reactions and content. We adopted a statistical analysis for the reaction-based measurement. We leveraged an LDA-based Topic Modeling Approach for content-based measurement. Our findings emphasize the significance of the existing social signals and user-generated content in the Algerian context.

1 Introduction

Several companies harness the potential of Online Social Networks (OSN). OSN present an effective communication channel between the company and its customers (Anubha and Shome, 2021; Santoso et al., 2020; Voorveld, 2019). Indeed, these social networks, tremendously, scale up the network effect of standard marketing techniques such as Word-Of-Mouth. Thereby, the emergence of Social Media Marketing (SMM). Indeed, SMM has become an independent field of marketing for which many

opportunities have been recognized: i) raising public awareness about companies, ii) product development through community involvement, by analyzing User-Generated Content (UGC) and gathering experience for the future steps (Richter et al., 2011).

The analysis of UGC in social networks has fundamentally reshaped marketing strategies. Users have unlimited freedom to express their opinions through different interactions (e.g. reviews, like, rating. . .) on web resources. This rich source of social information can be analyzed and exploited to serve several applications in various contexts. In particular, opinion mining and sentiment analysis techniques that have the ability to reveal users' behavior or reaction regarding an item or event. This knowledge represents the bedrock to build an effective content-based recommender system (Zatout et al., 2019).

Users/Brand owners' Engagement analysis and measurement in Arab-world companies seem to be falling behind and show somewhat shy usage. This paper investigates the existence and magnitude of social Media Marketing and explores the nature of both companies' and users' engagement. We also focus on the analysis of textual User-Generated Content in order to present some of their salient features by answering the following questions:

- Are there enough social data on Algerian productivity that can be harnessed to improve Recommender systems applications?
- What are the most used social signals?

Table 1: Details on some User/Brand Engagement studies.

Work	Dataset	Platform	Metrics and Factors
(Pletikosa Cvijikj and Michahelles, 2013a)	100 Brand pages	Facebook	Content type, Media type, posting day and time
(Olczak and Sobczyk, 2013)	10 pages belongs to 4 mobile brands	Facebook	Number of likes, number of shares and posting time.
(Jayasingh and Venkatesh, 2015)	10 169 Posts of 134 Brand pages	Facebook	Number of fans, Customer interaction and Posts type
(Yang et al., 2019)	12K posts of business pages of 500 companies in 6 industries	Facebook	Number of likes and posts' linguistic features, poster characteristics, post context heterogeneity.
(Aldous et al., 2019)	3 M social posts from 53 news organizations	Facebook, Instagram, Twitter, YouTube, and Reddit	shares, external posting, Topic variations

- How are Algerian Brand owners exploiting Social Media?
- How are the users engaging in Social Media Marketing?
- Is social data quality significant to build learning models? Such as Ranking Algerian products, Predicting some economic phenomenon, etc.

The rest of this paper is structured as follows. In the next section, we present some background on Social Signals, concepts of Brand-communities and brand-owners engagement, and how they can be measured. In addition, we review some related work. In Section 3, we describe the followed process in this investigation, starting from the targeted sample of data to the data analytics step. Section 4 is dedicated to reporting results and findings with discussion. We conclude in Section 5.

2 Background and Related Work

In this section we give some preliminaries on the engagement of brand-owners and their brand-communities (users) through social signals and how this engagement can be measured. Then, some related work are discussed.

Engagement in social media, is a multifaceted complex phenomenon that can be measured by a number of potential approaches (Lalmas et al., 2014; An and Weber, 2018) : i) Self-Reporting Approaches ii) Physiological Approaches and iii) Web Analytic

Approaches. This latter refers to the extraction of parameters thought to influence users' engagement, from the digital traces (UGC) left by users while interacting with a website. The most popular UGC on the Web are social signals such as comment, tag, Emotion, Post Message, Reaction, Share, vote, etc Most of these signals are mainly introduced to enable users to express whether they support, recommend or dislike a content (text, image, video, etc.). We can distinguish between social activities' actions and reactions. The actions (e.g., like, share) with counters indicate the rate of interaction with the Web resource. While the reactions, introduced last years, are emotional signals that allow users to interact with posts in a quick way using one of the reactions(Like, Love, Haha, Wow, Sad, and Angry) to react even if the content is difficult to like, as in the case of gloomy news.

Concerning the metrics, for *i) Brand Engagement*, we consider the metrics related to brand's posts: Content and Media Type and their related users interactions. While for *ii) User Engagement*, the considered metrics are: Reaction rates, the relevance of textual generated content regarding the related Brand/service.

Considering the scarcity of investigations on measuring Brand/User engagement for the Algerian Brands, we have narrowed our literature review to some related work from the Western world (Pletikosa Cvijikj and Michahelles, 2013a; Jayasingh and Venkatesh, 2015; Olczak

Table 2: Corpora for Algerian Social Data.

Corpus	Purpose	Corpus Details	Available
<i>Algerian Lexicon</i> (Mataoui et al., 2016)	Sentiment Analysis	206 posts, 7698 comments, Manually collected and annotated	No
<i>ARAACOM</i> (Rahab et al., 2017)	Opinion Mining	Comments on Algerian newspaper	No
(Soumeur et al., 2018)	Sentiment Analysis	20 Algerian brand pages, 25475 annotated comments.	No

and Sobczyk, 2013; Yang et al., 2019; Aldous et al., 2019). Table 1 gives some details on the used metrics and factors. The salient remark is that most used metrics are based on quantitative measurements, namely, the number of reactions and posting times. For news organisations, Aldous et al. (Aldous et al., 2019) defined a more efficient engagement metric based on the user behavior leading to external posting (Spreading content through public sharing to other public networks or platforms). This is performed by means of studying topic variation.

Concerning related work from a Natural Language Processing (NLP) point of view, we can consider that there is a lack of statistical and content analysis of social signals in the Algerian context. For that, we restricted our review to some Algerian online content corpora built for the purpose of content-based analysis, mainly opinion mining and sentiment analysis.

For the sentiment analysis purpose, Mataoui et al. (Mataoui et al., 2016) have built a dataset for Algerian dialect from some main frequented Algerian pages. The chosen social signals are textual (text of posts and comments). They have annotated the dataset manually and they built three Algerian lexicons.

Rahab et al. (Rahab et al., 2017) have built ARAACON (ARABic Algerian Corpus for Opinion Mining), a corpus of comments collected from online Algerian Arabic journals. These comments are mostly written in Algerian Dialect.

From an economic side, recently, some studies, have investigated the impact of social media on digital businesses. For instance, Graa et al. (Graa et al., 2017) have studied the impact

of social media on Algerian purchase behavior. While (Abuljadail and Ha, 2019) have studied the impact of post content type (Hedonic and utilitarian benefits) on the engagement rate. However, these studies are done by means of traditional questionnaire surveys.

In (Soumeur et al., 2018), authors have focused on the specificity of Algerian dialect. They performed a specific pre-processing that improved the data quality. In order to perform sentiment analysis, they used two machine learning models: a Multilayer Layer Perceptron (MLP) neural network and a (Deep) Convolutional Neural Network (CNN).

3 Methodology

In this section, we present an overview of the followed steps, as illustrated in Figure 1. We start by data collection, followed by data preparation (annotation and pre-processing), then data analytics by means of some measured aspects.

3.1 Data collection

Considering the scarcity of datasets on Algerian social signals related to brands and their communities. We have been constrained to collect a sample that encompasses the most powerful and well known brands/services and industrial companies in Algeria. In addition to their visibility on Social Media. The dataset categorizes the collected Brands and Services according to their topic of interest.

Following a similar recipe to the one suggested by authors in (Bougrine et al., 2017). The sample dataset has been collected by following these stages:

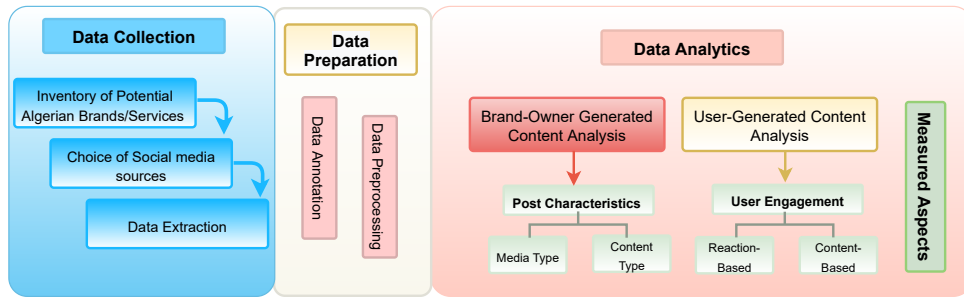


Figure 1: Methodology Overview

Table 3: Details on Chosen Brands and Services.

Category	Subcategory	#	Illustration	#Post	#Comment
Brand	Appliance	5	Condor Electronics, ENIEM, Cobra Electronics, ENIE, StartLight	1 247	21 786
	Beauty/Hygiene	4	Awane, Bimbies, finessecepro, Venus	577	
	Beverage	6	CAFE-Boukhari, Aroma-Café, Rouiba-Jus, Vita-Jus, Cevital-boissons, Ngaous	1 106	15 305
	Dairy	3	Soummam, FALAIT-Tartino, Berber-fromage	423	
	Electronics/Phone	4	LG Algerie, Oppo Algerie, Huawei mobileDZ, SonymobileDZ	937	
	Food	6	Benamor, Safina, Sim, CevitalCulinaire, Jumbo, Bimo	1451	
	Furniture	2	Dz-meuble, Sotrabois menuiserie d'art	199	31 398
	Household Goods	4	Nassah, El-Bahdjadetergents, Aigle, Force Xpress	347	26 576
	Industrial	4	Imetal-SIDER EL-ADJAR, SNVI, TEXALG ex. Sonitex, ENAP	81	256
	Industrial/Auto	2	Renault'DZ, Dacia'DZ		
Services	Accommodation	3	El-Djazair, ElAurassi, El Biar hotel	54	34
	Telecommunication	3	Djezzy'DZ, Mobilis, Ooredoo'DZ	1 960	665 284
	Transportation/Airlines	2	Air Algerie, Tassili Airlines	257	35 274
	Web Service	1	Ouedkniss.com	565	45 539
Total	14	50		9 977	906 705

1. Inventory of Potential Algerian Brands/Products/Services :

First, we have identified Brands/Products/Services that are the most representative of Algerian productivity. This is mainly done using direct expert advice and some social media analytic platforms such as Social-Bakers¹. This step leads to a preliminary list of Brands and services.

2. Inventory of Potential social Media sources:

we have identified the common social media platforms used by communities in concerns. Indeed, depending on their culture and preferences, some communities show preferences of some social media over

others. For example, in the time span of this study Algerian users are less interested in *Instagram* or *Snapchat* compared to Middle Est and Gulf communities. In fact, they commonly use Facebook and YouTube². These statistics show that from the period between January and November 2017 (the period of our dataset collection), Facebook represents the most used social media platform with 75.94% followed by Youtube and Twitter with only 11.37% and 8.28% respectively.

3. Extraction Process

In order to avoid collecting useless data. This step is achieved in two stages: (i) *Providing Lists*: We define the main keywords that can help automatically search targeted lists. When such lists are

¹www.socialbakers.com : social media analytics platform.

²http://gs.statcounter.com/#social_media-DZ-monthly-201601-201701-bar

established, a first filtering is performed to keep only the potential suitable data. It helps to enlarge our *Brand-list* by Brands that are well visible via Social networks (i.e. well ranked) but not considered by experts as a powerful Brand/Service. (ii) Downloading Data: in this step, we use customized scripts, and Facebook Graph API to scrape the data.

3.2 Data Annotation & Cleaning

We have prepared the data following two step, namely, annotation and cleaning. We manually annotated users' comments according to their:

- *Relevance* : we have considered two classes. Relevant: that says that the topic comments have relation with the targeted post and Irrelevant: which does not have any relation with the related post.
- *Polarity* : Positive, Negative or Neutral.
- *Language distribution and used scripts*: We have considered the most used languages for the Algerian community which are Modern Standard Arabic (MSA), the first and second foreign languages (French and English), and the Algerian Dialect as the common communicated language in the community. In fact, for each comment, we considered the ratio of words by language.

For the purpose of the textual content analysis, we adopted the following data-cleaning steps for all comments in our dataset. First, we remove all photos, stickers, and punctuations, keeping only textual data. Then, we remove stop words (Arabic and French stop words). After that we apply tokenization. We also remove emojis in a second round of cleaning the data.

3.3 Data Analytics & Measured Aspects

In order to investigate the nature and rates of both users and brands' owners engagements, we adopted two types of analysis considering

User Generated Content *UGC* and Brand Generated Content *BGC* respectively. In what follows, we demonstrate the considered metrics for both types.

3.3.1 UGC analysis

We addressed user engagement in two ways. One relies on statistical reaction-based analysis, where Engagement Rates consider simple metrics like the number of shares, comments, and reactions) (Pletikosa Cvijikj and Michahelles, 2013b; Perreault and Mosconi, 2018). The second metric relies on content analysis (linguistic features, comments' text analysis) where we deploy some (NLP) techniques to measure the quality and rate of the engagement. These techniques include applying Topic Modeling on comments using Latent Dirichlet Allocation model(LDA) 4.3) (Blei et al., 2003).

Furthermore, we measure the user engagement rate based on content analysis for post/brand using the relevance of users' comments regarding the post content. Thus, we suggest the following formulas:

First, the content-based engagement rate with a specific post *CPER* (1) metric.

$$CPER = \frac{RCP}{NCP} \quad (1)$$

Where *RCP* and *NCP* are the number of relevant comments per post and the total number of comments per post, respectively. We rely on Topic Modeling of comments' to achieve such goal(see Section 4.3).

Second, we measure the user engagement rate with a brand *CBER* 2 as an average of the total number of user engagement rate for all the posts of a specific brand *CPER* (1)

$$CBER = (\sum_{All\ posts} CPER) / NP \quad (2)$$

Where *NP* is the total number of posts per Brand.

3.3.2 BGC analysis

We perform an analysis related to post characteristics where we have considered:

- Content Type (CT) : we considered three classes: Information *Info.* about product/service, remuneration *Renum.* where competitions with rewards and offers are proposed, entertainment *Enter.* any pleasant and hedonic content and *other.*
- Media Type (MT): status, photo, video, link or event. Some media types keep the user more engaged like videos.

Another fundamental metric called *Post Engagement Rate PER* is considered. According to Facebook this metric has different ways of measuring. Bellow, the details about two of them :

$$PER = \frac{R + C + S}{f} * 100 \quad (3)$$

$$PER' = \frac{R + C + S}{Reach} * 100 \quad (4)$$

Where R is the total number of posts' reactions and C is the total number of posts' comments, S is the total number of posts' shares, f is the total number of followers on the day of posting. Although, the second formula gives a more accurate result than the first one, because it uses the *Reach* metric which is considered as a private data (visible only to the platform and the page owners). And it can't be applicable by simple users. Thus, we will only use the first Formula for this study.

4 Results and Discussion

As reported in Figure 3, the resulted chosen sample consists of 50 brands/Services pages with 9977 posts. It is worth mentioning that we have extracted posts with their related information that might be essential for our study like the number of comments, shares, and reactions. We have also scraped all posts' comments for 12 pages that belongs to different subcategories and their related user interactions. In total, we obtain around 900K comments.

In addition, to fairly assess these statistics, we have compared them to the 50 first well engaged world Brands as a baseline dataset with a similar distribution of Brands. This

latter is collected from the Website *Ranking the Brands*³. This Website presents statistics about the world most engaged brands. The data we used from this source was bound to the same period of collection of our Algerian Facebook pages data.

For some other metrics, we have relied on SocialBakers studies and those of Buffer and Buzzsumo⁴ which is considered as one of the largest studies, where they analyzed more than 43 millions Facebook posts from the top 20 k brands in the world⁵.

In order to interpret the results, we have chosen to separately analyse them on both sides : Users and Brands' Owners.

4.1 Brand's Owner Engagement

Concerning the engagement of Brands' Owners through their pages. We have examined three facts: the used media type (MT) in posts, content type (CT) and the post engagement rate metric (PER).

Figure 3a reports the distribution of all posts according to their media type (Event, Link, Photo, Status, Video) currently allowed by Facebook. While it is known that the richest media is Video as it describes the product or service better than a photo. We observe that the most used media by our chosen Brands is the "Photo" with more than 85% while only 8.5% of posts deploy videos. In addition, video posts are less used on the Algerian Brand/Service posts counter to the world baseline one with 46%. Furthermore, Event Type is the less used.

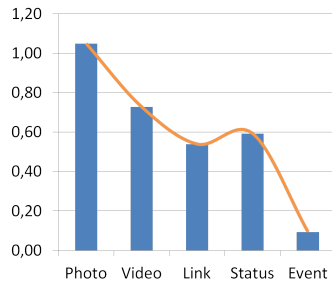
Figure 2 reports the average post Engagement Rates in term of MT for both Algerian's and the worlds' Brands/Services. According to these comparative results, we notice that Photos, which are the most used MT in Algerian brand/service posts, gives them the highest ER compared to others. We notice a considerable ER for videos and status. Even though they are less used.

Comparing the curve of Algerian ER in Figure 2a and the world baseline one in Figure 2b,

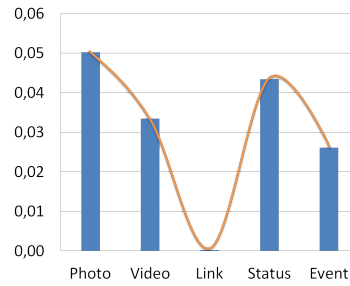
³<https://www.rankingthebrands.com>"

⁴<https://buzzsumo.com/>

⁵<https://buffer.com/7>



(a) Average of ER received by Algerian Brands/Services



(b) Average of ER received by World Brands/Services

Figure 2: Distribution of Posts & ER by MT (Algeria vs. World)

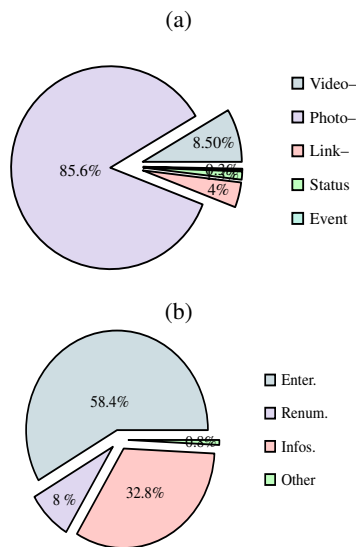


Figure 3: Distribution of Posts by (a) Media Type, (b) Content Type.

we observe that link MT gives a considerable ER for the Algerian sample, while this is not the case for the world baseline sample, counter to the event MT which gives high ER for worlds' Brand/Service posts and low ER for the Algerian ones.

Figure 3b reports the distribution of all posts according to the used Content type. These results show that most of Algerian Brand/Service posts have Entertainment Content Type, and just 8% of them have Remuneration Content Type. While we notice that information posts are the most published posts in the World baseline brands/services (60%) while they are less considered in the Algerian ones.

Comparing the curves of the worlds' ones in Figure 4b and the Algerian's ones in Figure 4a in terms of post ER according to the CT, we

notice that they have the same magnitude. In fact, the remuneration is the most attractive CT followed by Information Content Type for both Algerians' and worlds' posts samples.

By comparing the results reported in Figure 3a with those in Figure 4a, we notice that the most used CT is "Entertainment". However, the "Remuneration" and the "Information" ones bring higher Post ER than those of "Entertainment" in Algerian brand/service posts.

In summary, the engagement of Algerian brands' owners is quite significant.

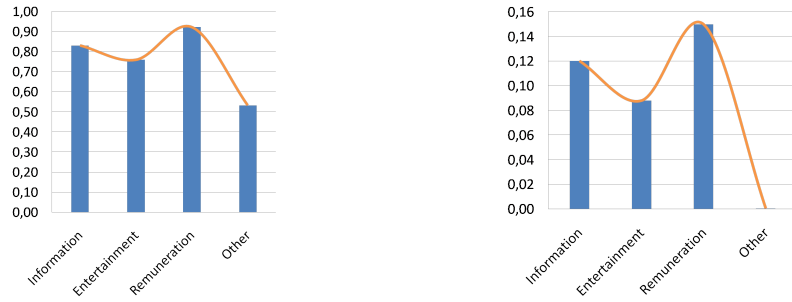
4.2 User' Engagement

For the user side involvement in social marketing, we have analyzed their interest through the quantitative and qualitative measure of interactions. In fact, a users' (potential consumer) comments can provide a better feedback and more information.

Figure 5a and Figure 5b report the distribution of users' interactions by type of deployed Social Signal and the distribution of emotional reactions, respectively.

We observe that users mainly use Reactions (more than 73%), while comments are used with a distribution of 23%. However, users are less active on sharing action. Even though sharing is considered as a deep level of engagement (Aldous et al., 2019).

A more fine analysis of emotional reactions, shows (Figure 5b) that Algerian users are less used to emotional reactions. This latter can be explained by the fact that the emotional reactions has been just introduced by Facebook



(a) Average of ER received by Algerian Brands/Services (b) Average of ER received by World Brands/Services

Figure 4: Distribution of Posts & ER by CT (Algeria vs. World)

at the time of collection of our dataset.

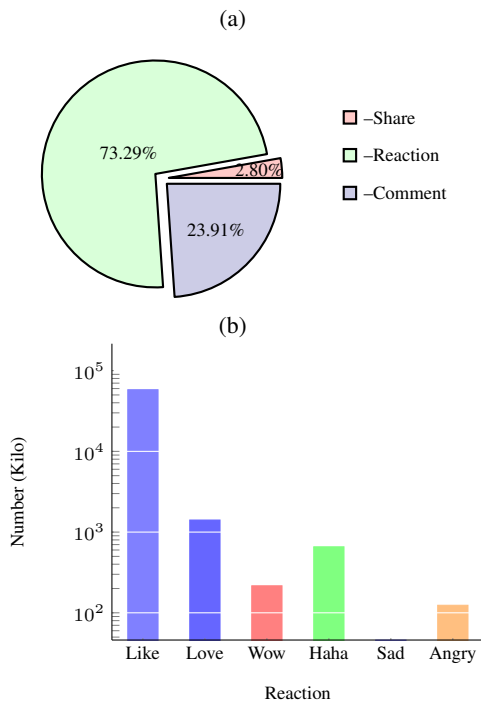


Figure 5: Distribution by type of (a) Social Signal (b) Emotional Reactions

4.3 User's content-based engagement

In addition to the previous statistical analysis of the collected data. We performed some textual data analytics using Topic Modeling. The aim of Topic Modeling here is to discover the notable topics discussed in comments and quantify to what extent users are engaged with a brand/service content. Differently put, Topic Modeling investigates the comments' relevance by checking similarities between the top words of the topic describing

a brand/service and the brand/service related comments. t

In the current work, we used Latent Dirichlet Allocation (LDA) method (Blei et al., 2003) that exhibits smooth scalability applied on large textual corpora.

Topic modeling here serves as an aggregation tool to discover the latent discussed topics in users' comments.

By examining the resulting topics presented in Table 4, we can clearly notice that they represent most of the Brand/service categories covered by this study.

For instance, most of the words in *Topic 0* are related to the Algerian Airlines company (i.e, most of the aggregated words are from *AirAlgerie* Facebook page. For example, The words: الله, *alger*, *paris*, *billet*, *bonne*, *prix*, *vol*, *air*, are respectively in English: *Allah* (the God), *Algiers* (the capital of Algeria), *Paris* (the capital of France), *Ticket* (the flight ticket), *good or nice* (we assume that it is a typo in writing "bon" from "bon voyage", *Nice trip*), *Price*, *Flight* and *Air* from the company name *AirAlgerie*.

Another example, is *Topic 4* which is about the two biggest telecommunication companies in Algeria: *Ooredoo* and *Mobilis*. Most of the words indicating that users' comments are about these companies services. Some of these words are: جيجا، موبيليس، تم، صالح، دج، *ooredoo*, *prix*, *max*, *win*, *da*. The English translation of the previous words, respectively is: *Dzd* (the Algerian currency), *valid* (most probably about the phone credit), *done* (a com-

Table 4: Example of generated topwords of a topic using LDA model.

Topic Number	Top words	Top words(English)	Description
Topic 0	air, الله , alger, paris, billet, bonne, algerie, bien, prix, share, site, mohamed, saha, da, vol, أيام	air,Allah(God), Algiers, Paris, ticket, good Algeria, price, share, site, Mohamed, okay, Dzd, flight, days	this represents the airlines Facebook page
Topic 1	hada, aroma , chaba , Mohamed , قهوة , top , تمانشاء, الله , اروما, روعة , المسحب , prix .	This,aroma,nice, Mohamed,coffee,top,price,lottery,fantastic,aroma ,God willing, done	This is the Aroma coffee Facebook page
Topic 2	merci, lg, participe, chance, produits, force, prix, aigle, bien, top, express, lave, xpress, شكرًا، الله ، الجزائر، الجي، مبروك.	Thanks, LG, participate, luck, product, force, price, Aigle, good, top , express, wash, xpress, congratulation, LG, Algeria, Allah, thanks	The cleaning stuff topic for AigleGroup, and Force Express Brands
Topic 3	ooredoo, prix , max , win, da, go , أوكتيه ، دج ، ساعة ، صالح ، موبيليس، وين، تم ، جيغا، شهر، الرسوم، الجواب	Ooredoo, price, max , win, Dzd, GO, valid, an hour, Dzd, octet, , the answer, fee, month, Giga, done,la win, Mobilis	This topic is about telecommunication companies Ooredoo and Mobilis

mon word used in the Algerian content indicating that someone has seen the post), *Mobilis* (the first company name), *giga* (or *gigaoctet*: a unit for computer memory), *Ooredoo* (the second company name), *Price*, *Max* and *Win*(plans names offered by the company), *Dzd*(the abbreviation of the algerian currency in french; *Dinar Algerien*).

We can also highlight the repetition of the word "الله" in most of the topics' word set. A possible interpretation could be that it is a very common for Algerian users to *overuse* the expression "إن شاء الله ، انشاء الله" English: *God willing* with all its variations, in their daily life, thus in their online comments .

4.4 Used Languages and Scripts

Concerning the used languages, Figure 6 illustrates their distribution in users' comments. It shows that French is the most used language, followed by MSA Arabic with 35.7% then Algerian dialect with 19.4%. The category "Other" includes Tamazight, Espagnol, Korean and others.

While for the distribution of used Scripts, we have classified comments according to Arabic scripts, Latin scripts, mixed Arabic, Latin scripts and other scripting sets like emoticons or numbers. We observe that 65% of textual comments use Latin characters while 25% of them use Arabic ones.

Moreover, we have analyzed the usage of Emojis where we have reported that just 7%

of Algerian customers' comments are using emoticons while 93% of them are textual.

These findings could help brands in terms of marketing get closer to their customers through understanding their language. In addition, these findings help any Natural Language Processing research problem to leverage such linguistic features.

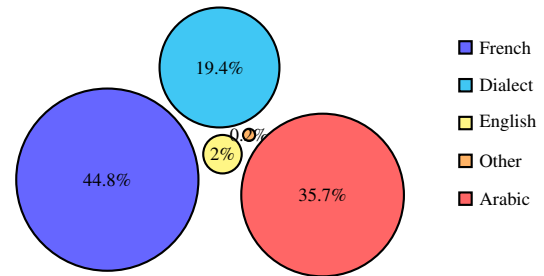


Figure 6: Distribution of used languages in User comments

5 Conclusion

We proposed an analytical study based on statistical and textual analysis of User/Brand Generated Content on social media. We investigated the level of Users/Brands engagement by two means: using the common User engagement formulas in the literature for reactions case. And we suggested a content-based user engagement approach based on LDA Topic Modeling method. Our finding highlights the quantitative and qualitative significance of the existing social signals in the Algerian productivity context. Which can efficiently help

Brands' owners to improve their productivity and online marketing strategy. In the future, we intend to normalise the whole content of the data set by, automatically detecting the language and translate it to Modern Standard Arabic. We will also investigate the effectiveness of Topic Modeling on assessing users' engagement.

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