Social Analysis of Young Basque Speaking Communities in Twitter

Joseba Fernandez de Landa, Rodrigo Agerri
HiTZ Center - Ixa, University of the Basque Country UPV/EHU
{joseba.fernandezdelanda,rodrigo.agerri}@ehu.eus

Abstract

In this paper we take into account both social and linguistic aspects to perform demographic analysis by processing a large amount of tweets in Basque language. The study of demographic characteristics and social relationships are approached by applying machine learning and modern deep-learning Natural Language Processing (NLP) techniques, combining social sciences with automatic text processing. More specifically, our main objective is to combine demographic inference and social analysis in order to detect young Basque Twitter users and to identify the communities that arise from their relationships or shared content. This social and demographic analysis will be entirely based on the automatically collected tweets using NLP to convert unstructured textual information into interpretable knowledge.

Keywords: Computational Social Science, Cultural Analytics, Natural Language Processing, Basque language, Demographic Analysis, Social media

1 Introduction

Basque is a low resourced language, spoken by 28.4% and understood by 44.8% of the population of the Basque Country (Eusko Jaurlaritza et al., 2016). Thanks to its official status, it is a language with presence in the regional public administration, education system and in some news media. Thus, in EiTB (Euskal Irrati Telebista), the Basque public radio and television broadcaster, it is possible to find radio and television channels in which all content is entirely broadcasted in Basque. Furthermore, there are other independent media such as Berria (newspaper), Argia (weekly magazine) and HamaikaTB (a television channel), in which Basque is the vehicular language. Still, the presence of Basque in traditional television and news media remains quite low, particularly when compared with those available for Spanish.

In this context, the increasingly used social networks such as Twitter are of particular importance for a low resourced language such as Basque. Thus, it is possible to find a strong and active community of Basque speakers in Twitter which generates, for a low resourced language, a large amount of textual content written on Basque. Furthermore, as users create both explicit and implicit relations and communities, this data is useful to do social research using methods that may complement those traditionally used in sociology (Baldwin et al., 2015; Nguyen et al., 2016; Rosenthal et al., 2017). Following this, a promising and relatively new avenue of research in social and demographic analysis combines the study of social structures created in media such as Twitter with the automatic analysis of texts via NLP. For example, previous work has focused on Twitter to study the spread of rumours (Derczynski et al., 2017), the detection of political stance (Mohammad et al., 2016) or hate speech (Basile et al., 2019).

In this paper we will take into account both social and linguistic aspects in order to perform demographic analysis by processing a large amount of tweets in Basque language. The study of demographic...
characteristics and social relationships will be approached by applying machine learning and modern deep-learning NLP techniques, combining social sciences with automatic text processing.

More specifically, our main objective is to combine demographic inference and social analysis in order to detect young Basque Twitter users and to identify the communities that arise from their relationships or shared content. By “Basque Twitter users” we refer to those that write at least 20% of their tweets in Basque. This social and demographic analysis will be entirely based on the automatically collected tweets using NLP to convert unstructured textual information into interpretable knowledge.

Current work substantially improves and extends the preliminary experimental work presented in (Fernandez de Landa et al., 2019). These improvements have led to a number of contributions. First, and taking as a starting point the Heldugazte corpus containing 6M tweets in Basque language (Fernandez de Landa et al., 2019), we devise a whole new methodology to classify users by life-stage (young/adult). This new method generates a new dataset, Heldugazte-Age, containing 80K tweets semi-automatically annotated at young/adult level. Second, we explore the application of modern pre-trained large multilingual and monolingual models (Devlin et al., 2019; Agerri et al., 2020) in order to identify young and adult users. Third, we perform a qualitative analysis comparing human performance vs life stage classifiers for classifying Basque users into the young or adult categories. Four, we use recently developed deep learning techniques for community detection, achieving better detection and visualization of the communities, as well as providing information of the relations among them. We believe that the methodology presented in this paper might be of interest for other NLP tasks and other types of social and demographic studies. Finally, we publicly distribute every resource (software and data) to facilitate further research for low resourced languages such as Basque.

The rest of the paper is structured as follows. In the next section we describe related work in computational sociolinguistics and NLP. In Section 3 we present our method to build the Heldugazte-Age annotated dataset to train classifiers for life stage detection. Section 4 presents systems used to train classifiers for life stage detection. These classifiers are evaluated in Section 5 and applied to perform social network analysis in Section 6. We finish with some concluding remarks and future work.

2 Context and Related Work

Social media offers the opportunity to express beliefs, sentiments or opinions in a variety of formats, including text, image, audio and video. Social media publications express conscious and/or subconscious manifestations of our social, emotional and rational condition.

Previous work in sociolinguistics argues that our writing style can even be a reflection of demographic characteristics (Nguyen et al., 2016). Considering the fact that language is a social phenomenon and thanks to the ever-growing capacity in the NLP field to collect and process large-scale amounts of texts, computational sociolinguistics is becoming increasingly popular. The widespread use of Twitter has in fact benefited such approaches as it is possible now to mine large amounts of texts also for less resourced languages.

Twitter is widely used in NLP for tasks such as mining opinions about specific products or topics (Vil-lena et al., 2013; Rosenthal et al., 2017), detecting political stance (Mohammad et al., 2016; Derczynski et al., 2017) and hate speech (Basile et al., 2019) or for basic tasks such as POS tagging (Ritter et al., 2011), named entity recognition (Baldwin et al., 2015), normalization (Alegria et al., 2015) and language identification (Zubiaga et al., 2016).

NLP techniques specifically adapted for Twitter have also been used to infer demographic characteristics such as gender, age or location (Cesare et al., 2017; Morgan-Lopez et al., 2017). Moreover, relationships, style shifting and community dynamics can also be inferred from language analysis (Nguyen et al., 2016). Of particular interest to us is the body of work performed with the objective of age or life stage detection for Twitter users. Previous works usually generate their own manually annotated datasets, covering languages such as Dutch, English or Spanish (Rao et al., 2010; Al Zamal et al., 2012; Nguyen et al., 2013; Marquardt et al., 2014; Morgan-Lopez et al., 2017; Zaghrouani and Charfi, 2018) for a user range between 300 and 3000. The best performing systems are those that model life stage classification.

https://github.com/ixa-ehu/heldugazte-corpus
as a binary (Rao et al., 2010; Al Zamal et al., 2012) or ternary (Nguyen et al., 2013; Morgan-Lopez et al., 2017) task.

In relation to the study of the social relationships that are generated within the network, closer to us are those studies that have aimed to identify communities of users based on their retweets. Among these, one can find studies about political polarization (Conover et al., 2011), political affiliation detection (Pennacchiotti and Popescu, 2011) or even studies about identifying communities in movements for independence (Zubiaga et al., 2017).

Finally, there are different research works investigating the use of low resourced languages within social networks. An investigation about Welsh (Cymraeg) speakers and Twitter, shows that speakers of this language are also active in social media (Jones et al., 2013). Additionally, there is another work that extracts and analyzes more than 80k tweets in Irish (Gaeilge) to do content, sentiment and network analysis (Mhichil et al., 2018). It is also interesting a study combining Welsh, Irish and Frisian (Frysk) to investigate the use of hashtags across 3,000 different tweets (McMonagle et al., 2019). All these works show the potentiality of Twitter to provide text data even for low resourced languages, giving the chance to find and study a huge variety of languages and cultures.

3 Heldugazte-Age: A New Dataset for Life Stage Classification

In this section we propose a new methodology to semi-automatically obtain labeled data to develop life stage classifiers. The result is a new dataset for to train classifiers for Life Stage Detection, namely, the Heldugazte-Age corpus.

The first step to identify online communities of young Basque speakers is collecting the data. As a starting point we will use the Basque corpus Heldugazte (Fernandez de Landa et al., 2019), which consists of 6M Basque tweets from 8,000 users, collected in May 2018. In this collection, the last 3,200 tweets from each user were retrieved (if available), including personal tweets and retweets.

The Heldugazte corpus will be used to semi-automatically generate a labeled subset of the corpus, 80K tweets, to train classifiers to detect young/adult users. The obtained classifiers will then be applied to the rest of the Heldugazte corpus to obtain a large number of tweets written by young users. This data will be used to detect the communities between young users.

In order to obtain a young/adult classifier we need some labeled data for training and evaluation. However, labeling users’ tweets by life stage is a difficult task, due to two main reasons: (i) users age hardly ever appear in the tweets metadata and, (ii) manually annotating tweets by life stage is far from being trivial. Examples (1-3) below illustrate the difficulty of manually labeling individual tweets by life stage and without any additional context.

(1) “Zarauzko triatloian izena ematea lortu gabe, motibazioa falta” I have not managed to sign up for the Zarautz triathlon, I am unmotivated

(2) “A zer nolako eguraldi kaxkarra ez al du gelditu behar edo” What a bad weather, shouldn’t stop or what.

(3) “5 mila euro, bideo kamera eta telefono mugikor bat eroan dituzte lapurrek” 5,000 euros, a video camera and a cell phone were taken away by the burglars.

In order to overcome this problem, previous sociolinguistic work has argued that writing style could be associated to author’s life stage, assuming that young people’s style is more informal than that of adults (Rao et al., 2010; Al Zamal et al., 2012; Nguyen et al., 2013; Morgan-Lopez et al., 2017).

Based on these previous works, Fernandez de Landa et al. (2019) trained various classifiers to distinguish between formal and informal writing style in tweets. Every tweet for every user in the Heldugazte corpus was automatically tagged, projecting from formal/informal to young/adult classification depending on the concentration of formal/informal tweets in each user’s timeline. The problem with this procedure was to objectively define a threshold for the proportion of formal/informal tweets required to

[^1]: http://ixa2.si.ehu.es/heldugazte-corpus/heldugazte-osoa.tar.gz
classify a user as young or adult. The proposed ad-hoc solution, establishing that if 45% of the tweets were labelled informal then the timeline was to be classified as young (adult otherwise) was far from ideal.

In this paper we propose a new method to objectively and semi-automatically obtain the labeled data required to train young/adult classifiers. The procedure is illustrated in Figure 1. First, we automatically tagged the 6M tweets in the Heldugazte corpus using the formal/informal classifiers developed by Fernandez de Landa et al. (2019). Second, we ranked users according to the proportion of informal tweets in their timeline. The top users would contain mostly informal tweets whereas the users at the bottom of the rank would consist mostly of formal tweets. Third, a manual inspection of 100 timelines (50 young and 50 adult) established that it was feasible to manually annotate users at both ends of the ranking as young/adult. In this step it was particularly helpful to perform the annotation at user-level because a full timeline provides more contextual information to characterize a specific user. Fourth, we took the 500 users at the top of the ranking to be young users and the 500 at the bottom to be adult. As a result, following this new method we obtain a set of 1,000 users (out of the original 8K users) classified as adult/young based on the initial formal/informal manual categorization of 1,000 tweets provided by Fernandez de Landa et al. (2019).

The final step consisted of randomly sampling a number of tweets per user. The idea was to vary the number of tweets and topics available per user providing a sample general enough to train robust young/adult classifiers. With this objective in mind, we picked 100 random tweets per user (if a user’s timeline did not contain at least 100 tweets then we used the full timeline) assigned to each of them the label attributed to the user (young/adult). As it is shown in Table 1, the final labeled set, Heldugazte-Age, contains 80K tweets equally distributed into the young and adult classes. The data was splitted for experimentation into a training (60%), development (20%) and test (20%) set, resulting, for each class, in 24K tweets for training and 8K for development and test, respectively.

|         | young | adult | total |
|---------|-------|-------|-------|
| users   | 500   | 500   | 1,000 |
| tweets  | 40,000| 40,000| 80,000|

Table 1: Annotated corpus for life stage detection at user level.
4 Life Stage Classification Systems

Here we present the two main systems used for life stage detection: (i) an off-the-shelf system based on linear classification and clustering features (Agerri and Rigau, 2016), and (ii) a deep learning approach based on learning contextual, vector-based word representations and the Transformer architecture (Devlin et al., 2019).

Previous approaches address life stage detection as a supervised text classification task (Rao et al., 2010; Al Zamal et al., 2012; Nguyen et al., 2013; Morgan-Lopez et al., 2017). This means that classifiers will learn, from annotated data, that a given tweet is written by a young or an adult person. An example of the dataset annotations used for training can be seen in Table 2. The Heldugazte-Age dataset developed in the previous section will therefore be used to train three different text classifiers: (i) IXA pipes (Agerri et al., 2014) (ii) multilingual BERT (Devlin et al., 2019) and, (iii) BERTeus (Agerri et al., 2020).

| Label | Content (tweet) |
|-------|----------------|
| adult | Taldeak mikel laboaren lanean oinarritu du bere hurrengo diskoa. The band has based their next album on the work of Mikel Laboa. |
| adult | Gure herriko ateak zabalik dituzu. The doors of our town are opened. |
| young | Buaa q follaa eun guzitia eon zea ikasi ordez jolasateeenn jajaja. How lucky! You have been all day playing instead of studying hahaha. |
| young | Batzutan ze gutxi aguantatze zaituten. Sometimes I can’t stand you. |

Table 2: Examples taken from the Heldugazte-Age dataset.

4.1 IXA pipes

IXA pipes is a set of tools with a multilingual approach across NLP tasks. This system has been successfully used in several sequence labelling tasks for various languages, including Named Entity Recognition (Agerri and Rigau, 2016), and Opinion Target Extraction (Agerri and Rigau, 2019).

The general objective of IXA pipes is to provide a general semi-supervised approach that performs well across languages and tasks. This approach consists of two different components. In the first one a set of linguistically shallow features are extracted from the local context; these features are based on orthographic and ngrams and character-based information to capture multi-word patterns and prefixes and suffixes of words, which has proven useful to work with an agglutinative language such as Basque (Agerri and Rigau, 2016). The second, semi-supervised, component injects external knowledge previously obtained from the unsupervised induction of clustering models over large amounts of texts. This component provides several benefits. First, it generates denser document representations, given that a document is represented with respect to the number of dimensions (clusters) specified in the obtained clustering model. Second, by training the clustering models on source data from different domains and text genres it is possible to inject domain-specific knowledge into the system. Finally, IXA pipes includes the possibility of including features from three types of clustering models (Brown et al., 1992; Clark, 2003; Mikolov et al., 2013), which helps to represent domain-specific information via complementary semantically induced knowledge. More details can be found in (Agerri and Rigau, 2016). For this particular work we train the IXA pipes document classifier using the same experimental setup used in (Fernandez de Landa et al., 2019).

4.2 Transformer Models

As for many other NLP tasks, current best performing systems for text classification are large pre-trained language models which allow to build rich representations of text based on contextual word embeddings. Deep learning methods in NLP represent words as continuous vectors on a low dimensional space, called word embeddings. The first approaches generated static word embeddings (Mikolov et al., 2013; Bojanowski et al., 2017), namely, they provided a unique vector-based representation for a given word
independently of the context in which the word occurs. This means that polysemy cannot be represented. Thus, if we consider the word ‘bank’, static word embedding approaches will generate only one vector representation even though such word may have different senses, namely, ‘financial institution’, ‘bench’, etc.

In order to address this problem, contextual word embeddings were proposed. The idea is to be able to generate word representations according to the context in which the word occurs. Currently there are many approaches to generate such contextual word representations, but we will focus on those that have had a direct impact in text classification, namely, the models based on the Transformer architecture (Vaswani et al., 2017) and of which BERT is perhaps the most popular example (Devlin et al., 2019).

There are several multilingual versions of these models. Thus, the multilingual version of BERT (Devlin et al., 2019) was trained for 104 languages. More recently, XLM-RoBERTa (Conneau et al., 2019) distributes a multilingual model which contains 100 languages. Both include Basque among the languages.

These multilingual models perform very well in tasks involving high-resourced languages such as English or Spanish, but their performance drops when applied to low-resourced languages (Agerri et al., 2020). Although this is still an open issue, a number of reasons can be found in the literature. First, each language has to share the quota of substrings and parameters with the rest of the languages represented in the pre-trained multilingual model. As the quota of substrings partially depends on corpus size, this means that larger languages such as English or Spanish are better represented than lower resourced languages such as Basque. Moreover, multilingual models also seem to behave better for structurally similar languages (Karthikeyan et al., 2020).

BERTeus (Agerri et al., 2020) is a language model trained in Basque language following BERT’s architecture (Devlin et al., 2019). They show that training a monolingual Basque BERT model obtains much better results than the multilingual versions. In this paper we will compare the performance of multilingual BERT and BERTeus for life stage detection using the same hyperparameters as in Agerri et al. (2020).

5 Life Stage Detection

In this section we will use the Heldugazte-Age corpus to train the classifiers previously described. The best classifier will then be applied to the whole Heldugazte dataset in order to obtain a young/adult classification of the 8K Basque tweet users contained in the corpus. Additionally, an analysis of the results is performed to better understand the quality of the semi-automatically obtained annotations.

5.1 Experimental Results

It should be noted that, in contrast to our previous work (Fernandez de Landa et al., 2019), the Heldugazte-Age corpus allows us to directly classify users as young/adult, without having to perform the formal/informal step.

We perform minimal pre-processing on the tweets; we remove URLs, hashtags and usernames, leaving label-tweet pairs such as the examples shown in Table 2. This procedure has proven to be useful in previous text classification works with tweets (Agerri et al., 2020; Zotova et al., 2021).

Table 3 reports the results obtained using the three systems described in Section 4. The high scores show that our semi-automatic method to obtain young/adult training data produces good quality annotations. Furthermore, the differences between the systems are not that large, although BERTeus is consistently the best scoring model.

| System    | Accuracy | Precision | Recall | F1 Score |
|-----------|----------|-----------|--------|----------|
| IXA pipes | 0.956    | 0.977     | 0.935  | 0.955    |
| mBERT     | 0.955    | 0.972     | 0.936  | 0.954    |
| BERTeus   | **0.963**| 0.968     | 0.958  | **0.963**|

Table 3: Evaluation results of young/adult classifier models on the Heldugazte-Age test set.
In order to further test the robustness of our semi-automatic method, described in Section 3, we decided to manually annotate 200 randomly selected tweets. Two human annotators labeled the 200 tweets and we calculated an agreement between the annotators of 0.78 and a Kappa score of 0.55, showing a moderate agreement between them. Furthermore, the accuracy of the two annotators are 0.795 and 0.775 respectively. When comparing these scores with the results reported in Table 3, it is clear that manually annotating young/adult at tweet level is a very difficult task. These results also show the effectiveness of our method to obtain the Heldugazte-Age corpus.

In the rest of this paper we will use the BERTeus fine-tuned model to automatically annotate the whole Heldugazte corpus. It should be noted that the classifier works at tweet level (as shown by Table 2). This means that once every tweet is automatically annotated, we still need to decide whether each of the user timelines corresponds to a young or adult user based on the number of individual tweets classified as young/adult.

5.2 Labeling the Large Corpus

Once the tweet classifier is ready to use, we apply the following strategy to automatically annotate the tweets in the Heldugazte corpus. First we assign a discrete young or adult label to each tweet. We then obtain a single score by averaging the number of the young/adult classified tweets of each user’s timeline.

The last step is to decide whether a given timeline corresponds to a young or adult user based on the score obtained from the classification of the individual tweets. In order to avoid establishing an ad-hoc value as a threshold, we introduce a third class for classification. In other words, a new synthetic category, “underdetermined”, is created thus transforming a binary task into a ternary one.

Based on the new ternary task, two thresholds are used instead of one, located at 60% and 40% of the number of tweets annotated as young in each timeline. Thus, if the proportion of labels or the average probability is over 60%, the user will be defined as a young user. On the other hand, if those values are lower than 40%, the timeline will be considered to be from an adult user. Finally, if the value is between 40% and 60% we will consider the timeline to be “underdetermined”, meaning that we do not have enough evidence to decide the life stage of the user. Adding the underdetermined class has the benefit of avoiding to commit ourselves to classify difficult cases as young/adult.

We are also interested in comparing the distribution of young/adult users obtained using the described procedure with those that are obtained using our previous method (Fernandez de Landa et al., 2019). As a reminder, in our previous work each tweet is classified as formal/informal and then, based on the number of informal tweets we decide whether the user is young or adult. However, for a fair comparison we will adapt it to use two thresholds (60/40 for young/adult) and three classes, as it has been described above.

|               | Adult | Underdetermined | Young |
|---------------|-------|----------------|-------|
| Previous system | 5,213 | 911            | 962   |
| New system     | 4,472 | 980            | 1,635 |

Table 4: Classifying users in terms of age stage (young/adult).

Table 4 shows the number of timelines classified as young/adult or underdetermined using our new and old methods. It can be seen that the main difference corresponds to the quantity of young users obtained by each of the methods. In the next subsection we further look into this issue.

5.2.1 Comparison of Methods

In this section we look at those variations in the automatic annotations assigned by the old method (Fernandez de Landa et al., 2019) with respect to the one presented in this paper. Table 5 shows the differences of classifying the timelines using the old (based on formal/informal classification of tweets) with respect to the the new method (based on young/adult classification). After a superficial look to the variations, it can be seen that 21.79% of the labels were differently labeled from previous to new system,
a substantial difference. Besides, one of the most significant variations is the increase in the amount of users labeled as young.

| previous to new |          |
|-----------------|----------|
| adult to adult  | 4325     |
| adult to und*   | 679*     |
| adult to young* | 209*     |
| und to adult    | 133      |
| und to und      | 285      |
| und to young*   | 493*     |
| young to adult  | 14       |
| young to und    | 16       |
| young to young  | 933      |

Two of the three most important variations, marked with an asterisk, refer to the transfer of timelines to the young class. It is also important the transfer from adult to underdetermined. Taking a deeper look into these specific cases, we manually inspected some randomly chosen timelines to see if these transfers are actually true positives or whether they are misclassifications. The objective of this comparison was to study the transfer of classifications across categories (from adult to young, for example) when using the new classification method. More specifically, we analyzed a random sample of 10% of the cases for each variation.

Below we can see example tweets from three different users. With respect to @user2 and @user3, they show that our new method, as opposed to the old one, actually classifies correctly their timelines. Thus, by looking at their tweets it seems that the users are indeed young, based on the writing style but also because the tweets talk about exams, an activity usually related to young people. The case of @user1 is more contentious, as it seems too difficult to establish the life stage of the user based on those examples, which is why the underdetermined classification does not seem misplaced.

- Adult to underdetermined variation example, @user1:
  - tweet_1a: A zer nolako eguraldi kaxkarra ez al du gelditu behar edo. *What a bad weather, shouldn’t stop or what.*
  - tweet_1b: Gu erakusteko prest, etorri daitezela lasai eskuzabalik hartuko ditugu eta. *We are ready to show it, we will wait for them with open arms.*

- Adult to young variation example, @user2:
  - tweet_2a: Horrelakoekin gustua ta guztien hartzen zaio ikasteari. *With this, you take pleasure in learning.*
  - tweet_2b: Buenobueno ba ikasiko dut gehio jaja ta ikusikozu gaindituko dutt jaja. *Weeell weeeell, I’ll learn more haha and you’ll see if I can pass the exam haha.*

- Underdetermined to young variation example, @user3:
  - tweet_3a: Ze txupi txatxi no me da la nota. *Awesome I don’t get to pass...*
  - tweet_3b: Ai naiz rayatzen pixkat asko con la mierda de la uni. *Oh I’m going crazy a little bit with university shit.*

Figure 2 depicts the variations in the classification from the using the old method (left) with respect to the new one (right). The manual inspection performed would indicate that such variations are in fact correct. In other words, it would seem that the method introduced in Sections 4 and 4.2 to develop classifiers to automatically annotate users in the Heldugazte corpus as young/adult/underdetermined produce better results.
6 Relationship network

In this section we will study the relations that appear between Basque young Twitter users. The starting point will be the retweets of messages written in Basque by the 1,635 users classified as young in the previous section. We select the retweets because they are the type of interactions between users that can show correlations better than other interactions such as mentions (Conover et al., 2011). Specifically, from the 418,903 retweets of the 1,635 young users, we extracted 24,837 nodes and 148,304 edges or connections. The nodes correspond to the users doing the retweets (our sample of 1,635 users) but also different users receiving them (from our sample or not). On the other hand, the edges represent if a source user has retweeted one or more times another target user, representing the connections in the graph.

Once the retweets are gathered we proceed to transform the unstructured data into a readable graph. First, we created a giant graph using the data (retweets) from each user. To build the graph, two features extracted from each retweet were used: (i) the retweeter and (ii) the user retweeted. After extracting the data, the visualization of the graph was created using the gephi program (Bastian et al., 2009). Second, we gave the network a spatial structure by using the ForceAtlas2 algorithm (Jacomy et al., 2014), ordering the nodes according to the established relations. This algorithm displays a spatialization process, giving a readable shape to a network with the aim of transforming the network into a map. This technique simulates a physical system in order to spatialize a network. As a result of this process, those nodes that are unrelated repulse each other, while related ones will attract each other. The algorithm can turn structural proximities into visual proximities, allowing the analysis of this particular type of data based on interactions. Thus, the relations can be displayed in a (huge) graph.

After creating the graph, we focused on two different aspects. First we identified the most important nodes of the network, to establish which users are the most influential. In a second step we uncovered the implicit communities of Basque users, splitting the huge graph into more readable subgroups that allowed us to infer the communities of young people.

6.1 Basque influencers among young users

The most retweeted users of the graph can reveal important characteristics of the investigated sample. The most important nodes show which users are the leaders for our sample. Thus, in Table 6 we can see the top 15 most retweeted users, based on two different classifications. On the one hand, there are those users with most overall retweets (Table 6a). On the other hand, we have the users that have been retweeted by different young users, focusing on how many different users have retweeted these users (Table 6b). These two rankings illustrate which users are actually the most influential between young Basque Twitter users.

By looking at the obtained rankings, we can see that at the top there are accounts related to Basque media: @berria (newspaper), @argia (weekly magazine), @naiz_info (newspaper), @topatu_eus (digital media related to young people), @HamaikaTb (a television channel), @euskaltelebista (Basque public television broadcaster) and @LeakoHitza (local newspaper); and Basque journalists: @larbelaitz, @axierL, @boligorria (the three of them journalists from Argia) and @IBROKI (sports journalist in the Basque Television). We attribute this to the fact that those people perform important roles in the creation and distribution of Basque language content in the Web.

After a manual analysis of the obtained influencers, it has to be said that only two of them are accounts related to young people: @ernaigazte and @topatu_eus are both accounts related to organizations formed by young people. On the one hand, @ernaigazte is the account of the Basque nationalist left youth organization, named Ernai. On the other hand, @topatu_eus is a digital media account related to young people, very related to the Basque nationalist left. The lack of influencers among young users, could be related to the characteristics of Twitter, which is mostly structured around to political issues.

6.2 Basque speaking communities for young users

Once the main network graph was created, we split it into subgroups to analyze how the sub-communities or subgroups inside each one are formed. We divided each graph into subgroups using the node2vec algorithm (Grover and Leskovec, 2016), which allows us to obtain consistent subgroups. The node2vec
algorithm can freely explore network neighborhoods which is useful to discover homophilic communities. Unlike modularity based algorithms (Blondel et al., 2008), used in a previous analysis of Basque communities (Fernandez de Landa et al., 2019), node2vec gives the opportunity to choose the exact number of communities to be extracted. Besides, this algorithm can be tuned in order to give more importance to homophilia or to structural equivalence. Thus, Figure 3 shows that node2vec generates clearly distinguishable sub-communities, which in turn makes them more interpretable thereby facilitating the understanding of the existing relations between them.

After splitting the graph into four communities, we had to infer the main characteristics of each subgroup. For this process we focus again on the most important nodes which are the ones used to define the community itself.

Each of the subgroups displays a common characteristic, namely, all of them have a direct relation with topics or issues related to the Basque Country. Those topics are different in each of the subgroups in the graph, showing the characteristics or differences of each community. Thus, it can be seen that Basque language interactions are used to talk about various Basque current affairs (news) and politics (Nationalist left). Also, it can be seen that music and sports are also widely commented by young people.

In other words, it seems that the main function of Twitter interaction is to spread content about politics and social issues but with a clear focus on the Basque community and language. In the following we describe the main characteristics of each of the four subgroups contained in the graph.

• **News** (29.96%): In this community, the nodes found at the top of the ranking are related to news media from the Basque Country (@berria, @arga, @HamaikaTb, @eitbAlbistek, @euskaltelebista, @zuzeu, @euskadi_irratia, @Gaztezulo, @Sustatu, @eitbeus...), specific Basque journalists (@MaddalenIriarte, @boligorria, @urtziurkizu, @zaldieroa, @bzarrabeitia, @AneIrazabal... ) and also to other very active users that write about the most noteworthy news in Basque (@ielortza, @kalaportu, @KikeAmonarriz, @maia_jon...).

• **Nationalist left** (26.98%): The composition of this particular subgroup is characterized by nodes related, in different ways, with the nationalist/independentist Basque left. The nodes can refer to news media (@naiz_info, @topatu_eus, @info7irratia, @AhotsaInfo...), political and social organizations (@ernaigazte, @GureEskuDago, @AskeGunea, @ehbildu, @sortuEH, @EtxeratElkartea... ) and politicians from the main parties in this political movement (@ArnaldoOtegi, @jpermach...).
• **Sports** (22.58%): In the Sports subgroup the most important nodes are actually journalists (@iBROKI, @XabierEuzkitze, @Imagreto, @TxeetxuUrbietx, @jontolest, @unaizubeldia...) and news media (@eitbkirolak, @ukHitza, @3ErregeenMahaia...) specifically specialized in the sports domain. Thus, for this specific group the top accounts also refer to newspapers and television broadcasters. Other important nodes here are those related to sport teams, such as football teams (@RealSociedad, @RealSociedadEUS, @SDEibar, @AthleticClub...) and Basque ball clubs (@ASPEploeta...) or their players, which are mostly footballers from professional teams (@InigoMartinez, @mikelsanjo6, @ilara4...) or even well known cyclists (@AmetsTxurrekua, @mikelastarloza, @Markelirizar...).

• **Music** (20.49%): In the Music subgroup appear in prominent places music bands or singers which sing in Basque (@ZuriHidalgo, @vendettaska, @hesiantaldea, EsneBeltza, @gatibu, @ZeEsatek...), although other accounts related to music seem to be also very active (@GustokoMusika, @eusalkantak5, @KantuBatGara...).

Figure 3: Young users graph divided in communities.

Figures 3a and 3b show that young Basque users generally interact with users related to social issues (politics and news) as well as with those related to leisure (music and sport). Due to the new method applied for community detection, we are able to map the communities in a more consistent way, showing in a clear way where each community is located. The position of each community on the graph and the closeness between communities show how related the topics are between them. In this way we can see that communities related to social issues are next to each other, while the same occurs with the leisure-related communities. The community related to politics is close to news and music, illustrating both the relation with current news and the political stance of some Basque music bands. Besides, in three of the four communities (News, Nationalist left and Sports), media and journalists are referential, proving again that media is important at disseminating Basque content among young people, in spite of the main topic of the community.

In this section we show that combining the community detection algorithm and the visualization of the spacial representation of the graph, humans can easily interpret the meaning and characteristics of the displayed data. Thus, any information based on user interactions could be displayed and interpreted using these techniques, helping us to transform unstructured information into knowledge.
7 Concluding Remarks

In this paper we have presented a new methodology to perform demographic analysis by processing a large amount of tweets in Basque language. We have applied machine learning and deep learning approaches to Natural Language Processing to extract structured knowledge from unstructured data.

Our experimental results have shown that our new method produces good quality labeled data for training young/adult classifiers. This allows us to generate a new dataset of 80K tweets annotated at user level, namely, *Heldugazte-Age*. The analysis of the classifiers performance has shown that, when compared with manual annotations at tweet level, the annotations of our semi-automatically generated *Heldugazte-Age* dataset benefit from taking into account user-level information. Furthermore, we have experimented with modern deep learning techniques for NLP and for the detection and visualization of communities in Twitter. The use of these technologies has allowed us to get more consistent and readable results than in our previous approach (Fernandez de Landa et al., 2019), apart from a better understanding of communities and their interactions.

As a result of our new methodology, we have seen that the young Basque users can be grouped in four main communities. Furthermore, we have also seen that the most influential accounts among young users are related with Basque media, revealing the importance of this actor at disseminating content in Basque among the youngest. A general conclusion has been that Basque is mostly used in Twitter to speak about Basque-related topics, being that news, politics, sport or music.

We believe that the methodology presented in this paper might be of interest for other NLP tasks and other types of social and demographic studies. Finally, we publicly distribute every resource (software and data) to facilitate further research for low resourced languages such as Basque.

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