Damegender: Towards an International and Free Dataset about Name, Gender and Frequency

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Abstract

Equality of gender is the 5th objective of sustanaible development in United Nations[1].

This equality can be reached working on measure and analyze data and to apply politics from the results. On many gender studies, we need to count males and females deciding gender from names, for instance, research papers, job positions, streets, ... The traditional way is to use commercial APIs with propietary data without idea about how the data has been built. Another way, is taking data from wikipedia or scientific sites.

With Open Data idea, many statistics institutions are providing Open Datasets about name, gender and frequency. So, we need a scientific discussion about unifying formats, make easy ways to process these data and ways towards make standards. In this discussion, we take into account minorities, for example, LGTB claims such as attending the non binary reality.

The dataset is covering more than 20 countries in the occidental world. Having more names than any open source software in this moment. Allowing to measure gender gap to students and academics interested on the phenomenon.

There are a warranty of quality on reproducible research the citation about official sources provided by statistics institutions making easy the peer review and opening doors to the semantic web and the attention to minorities such as trans gender people, or cultures with own languages in states with another main language doing more cheaper to measure the gender gap.

1 Introduction

In recent times, many research investigations have been made on gender diversity in the IT domain. Examples of these efforts range from the participation in Twitter [BHKZ11, MLA+11], in Wikipedia [AYCN11, HS13], in science [HSFH18, DG99], and more specifically in the software domain in StackOverflow [VCS12, VPR+15], GitHub [VPR+15], and free software development [RARS+14, IHSR18, LC19, CPT+19].

The interest on gender diversity has become more and more relevant, and so does the identification methods that allow us to perform comprehensive studies on gender representation, given the large amounts of data available, in particular from collaborative environments.

The most used method to infer the gender of participants is by looking at their name. However, there are some studies about Twitter and GitHub where not only names are used to detect gender. In those studies we can find gender detection tools that infer the gender from faces in images [RPC17], from hand-written annotations [LSB11], or from speeches [KAS02].

Currently, there are different ways to detect gender from a person's name (and maybe other personal data, such as the surname, the geographic location, etc.). A first one is based on data extracted from the Wikipedia, self-references in trust websites, searches in Google Images, among others. Another way to do it is by using one of the existing Application Programming Interfaces (APIs). This paper is about the latter, focusing on their possibilities and limitations. Therefore, (i) we evaluate the quality (and accessibility, includ-

[1] https://www.un.org/sustainabledevelopment/gender-equality/

ing price) of different existing solutions; (ii) we discuss their limitations; and (iii) we investigate what happens with those names not included in a census, for example, nicknames or diminutives.

As a result, we contribute with: (i) an evaluation of the quality of different solutions applying well-known metrics;

(ii) a tool, called `damegender`, guessing gender from a name giving support to Spanish and English from the open data census provides by the states built to understand current technologies in detail; this tool has been compared with APIs using an international dataset with good results; and

(iii) a machine learning solution to strings not found in the census dataset to approach the problem with nicknames and diminutives;

The remainder of this paper is structured as follows:

In Section 2 we discuss the different ways to find evidence about names, gender and frequency.

Section 3 introduces the diversity discussion about minorities (cultural, LGTB, ...)

Section 4 is giving clues about how to approach the semantic web goals with the previous dicussion presented.

Section 5 reports on values of accuracy and offers a confusion matrix using a scientific dataset.

Section 6 is about how we use Machine Learning in `damegender`. Section 7 discusses limitations and further research, and concludes the paper.

2 Truehood and Falsehood in names, gender and frequency

The current idea in the field is the data about name, gender and frequency is ok because there are people who is paying by it, or many people is downloading a product. This intuition is right generally, although sometimes the people is paying by a bad product due to a good marketing strategy, a monopoly or there are a fraud, ... Another idea is the people trust in the goverment about statistics such as economy, demography, democracy, ... So the people can trust on names, gender and frequency. In Damegender, we are trusting in both notions about truehood: the market's point of view and the official statistics's point of view.

Sometimes there are problems downloading the official statistics but there are people who has retrieved these data, for example, with webscraping. We want classify these files with another idea about truehood.

Another problem arises when the goverment does little chances in the data, sometimes communicating it to the users and another times not. That could be a problem about upgrades, but it's not a problem with the truehood, although it's possible make a trace about this chances.

Another sources to retrieve gender and names can be personal scientific websites, wikipedia, or similar, but these sources is not giving the frequency, now. So, we are rejecting this idea.

With an international free dataset about names, gender and frequency we can build reproducible science in fields such as Natural Language Processing (gender detection from the name), social sciences (gender gap [HSFH18, MLA$^+$11]), lingüistic [LN05, Kru62, vdWRvdW$^+$20], software engineering [VCS12], ...

3 Gender, Language, Nation and Diversity

The first intuition about gender is male or female, but there non binary options about gender such as transgender that is changing laws in the goverments, so in some states a person can be registered as non male and non female. There are Open Datasets not provided by states about names classified as transgender. A good option is to wait the updates in laws and releases in open datasets with these non binary ideas. Meanwhile, it's possible to give to the users software to understand how many males and females is using a name.

Exists rules and exceptions in the languages to predict if a name is about male or female when you don't know the name. For example, in spanish or english there are more names ending with 'a' classified as females than classified as males. And Andrea is female in Spain and male in Italy. So, it's useful to understand the language and culture associated with a name. Language is close to nation, but there are differences, for example, in Spain there are several languages basque, catalan, castillian, ... or the spanish is the main language in Spain and in another countries such as Argentina, Mexico, Ecuador, Bolivia, ... So, it would be useful to detect the language and nation from names and surnames to help to detect gender.

Some countries, such as Spain, are providing free datasets about surnames but we need more efforts from many countries on this objective. On other hand, there are previous works to relate name and surnames with ethnicity using Wikipedia and Machine Learning.

4 Semantic Web

When we are describing people with names and gender could be giving semantic richness with semantic markup taking into account the lessons learned about the domain, for example, using microformats. Changing the current situation using a poor html:

```
<table class="infobox" style="width:22.7em;
line-height: 1.4em; text-align:left;
padding:.23em;">
  <tbody>
```

```
    <tr><th colspan="3" class="cabecera"
style="text-align:center;color:black;">
           Juan</th></tr><tr>
[...]
<tr><th scope="row"
style="text-align:left">
<a href="/wiki/Identidad_sexual"
   title="Identidad sexual">Género</a>
</th><td colspan="2"> Masculino</td></tr>
```

Towards the semantic way:

```
<div class="h-card">
  <span class="p-name">Emma Goldman</span>
  <span class="p-gender p-gender-female
               p-gender-female-us
               p-gender-female-inter">
         Female
  </span>
  <span class="p-street-address">
         123 Main St
  </span>
  <span class="p-locality">Some Town</span>
  <span class="p-region">CA</span>
  <span class="p-postal-code">90210</span>
</div>
```

With a richness markup take into account the gender in the context of a country.

5 Damegender Open Datasets Collection

In Damegender, we have unified the different formats to name, gender and frequency from official sources in these countries: Austria, Australia, Belgium, Canada, Denmark, Germany, Spain, Finland, France, Great Britain, Ireland, Mexico, New Zealand, Portugal and Slovenia.

Later, we have merged these datasets building a free and international dataset.

Generally, these data are providing name, gender and frequency about births (Canada), although in some countries (Spain) are giving the total.

We have found open datasets about countries such as Turkey and China retrieved by another open source developers that is being included in Damegender, but not in the international dataset. In Turkey the data has been retrieved using webscraping. And in China the data has been built by a company in collaboration with the China goverment and contributed to R language program. We want compare precision about this dataset with the commercial solutions to understand the truehood about these datasets.

When the work is finished, we could to rebuild machine learning models to predict new names and nicknames in any language and culture.

6 Measuring Gender Gap. GNU/Linux as Use Case

With a trust open dataset about names, gender and frequency is too easy to measure gender gap. Doing cheap to measure gender gap more students and academic people could work in the fith Objective Development Sustainaible of United Nations: to delete the gender gap.

This section is divided counting males and females in Debian, GNU and Linux.

We have reached the csv files from different ways to know the names about the people in these communities.

When this paper was being wrote in the Debian community all members must be collaborating with a gpg key, so we can count males and females from the keyring. The keyring was imported with gpg commands and later was dumped the keyring in a csv file.

In the moment to write this paper GNU[2] and Linux[3] has websites with the people collaborating in these projects. So, making webscraping scripts we have downloaded the people and processed the people to csv files

In Damegender, we have developed csv2gender, a software with a csv file as input and deploy a statistics graph and/or return the result of males, females and unknows about the input.

To make easy to reproduce the experiment we are pasting the commands used with the version 0.3.4 of damegender.

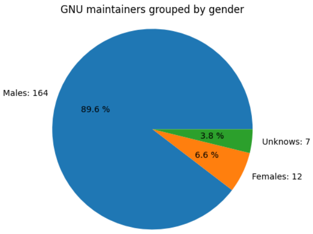
```
python3 csv2gender.py files/gnu-maintainers.csv
 --first_name_position=0
 --title="GNU maintainers grouped by gender"
 --dataset="inter"
 --outcsv="files/gnu-maintainers.gender.csv"
 --outimg="files/gnu-maintainers.gender.png"
 --noshow --delete_duplicated

python3 csv2gender.py files/linux-maintainers.csv
 --first_name_position=0
 --title="Linux maintaners grouped by gender"
 --dataset="inter"
 --outcsv="files/linux-maintainers.gender.csv"
 --outimg="files/linux-maintainers.gender.png"
 --noshow --delete_duplicated

python3 csv2gender.py files/debian-maintainers.csv
 --first_name_position=0
 --title="Debian maintaners grouped by gender"
 --dataset="inter"
 --outcsv="files/debian-maintainers.gender.csv"
```

[2] https://www.gnu.org/people/

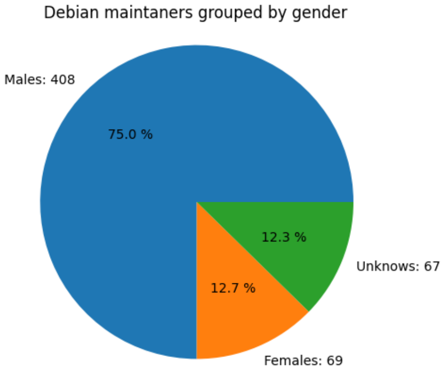
[3] https://www.kernel.org/doc/html/latest/process/maintainers.html

```
 --outimg="files/debian-maintainers.gender.png"
 --noshow --delete_duplicated
```

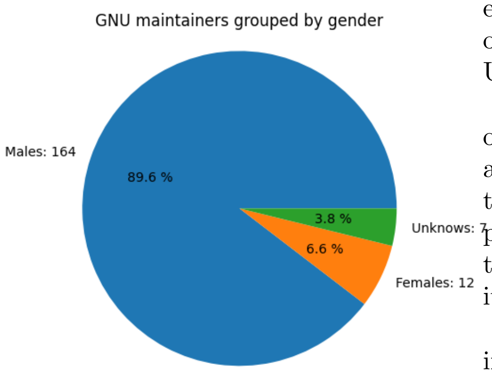
The inter dataset was created merging several open datasets downloaded from official statistics sites from different nations: Austria, Australia, Belgium, Canada, Germany, Denmark, Spain, Finland, Ireland, Iceland, Mexico, New Zealand, Portugal, Slovenia, United States of America, Uruguay and France. That's a good representation of the Western World and the Free Software world is populating this world's area



Linux divides the developers in 537 males (73.9%), 98 females (13.5%) and 92 unknows (12.7%). The number of unknows is due to different reasons, but it's so common in Linux that the developer is a company and not a name of a person.



Debian divides the developers in 408 males (75%), 69 females (12.7%) and 67 unknows (12.3%).



GNU divides the developers in 164 males (89.6%), 12 females (6.6%) and 7 unknows (3.8%)

The GNU people has a number lowest in females, they are the founder of the Free Software philosophy, the Debian principles and the Open Source philosophy was invented later influenced by GNU with very similar practical decisions (for example: deciding licenses for the software). Richard Stallman returned to be president recently apologizing by his personal behaviour with the females.[4]

7 Datasets

Name-to-gender inference services and tools apply several methods for estimating the gender from a given name. As a starting point, however, all of them rely on a dataset that contains information on what gender a name usually can be attributed to.

There are several sources to create these databases, being the most common: (1) a census published with a free license (open census way), (2) a dataset released with a free license in a free software package (free software way), (3) a dataset retrieved from commercial APIs (commercial API way), and (4) a dataset which is the result of an investigation and that has been released publicly (scientific way).

In damegender, we are including Open Data census about names and gender, usually offered by governments, such as the ones from Spain (by means of INE.es, the Spanish National Statistics Institute), Uruguay, USA and UK.

Some Open Datasets, such the one offered by INE.es or the government of the US offer support for surnames and how they are related to ethnicity. In particular, the dataset from the government of the US offers a probability of the race, and the Spanish INE.es gives the number of people with a surname with a nationality different to the Spanish nationality.

Generally, a name has a strong weight to determine if it is a male or a female using this procedure. For instance, David is registered 365,196 times as male, but 0 times as female in the data offered by the Spain National Institute of Statistics. There are names that heavily depend on the region. For instance, Andrea would be considered a female name in Germany, but a male name in Italy. Hence, we are using the census approach as base of truth to distinguish if a name is male or female in a geographical area. However, many countries do not provide Open Data census about gender and names, although our hope is that they will do in the near future.

We have evaluated to include data from the second option (datasets released with a free license). For instance, the Natural Language Tool Kit offers 8,000 labeled English names classified as male or female. Another example is Gender Guesser, which provides a good dataset for international names with different categories to define the probability. Although these datasets can be incorporated into damegender, the problem with them is that, in general, we have observed that they do not have the quality of National Statistics Institutes.

The third approach is to create the dataset from existing, usually commercial solutions. Here we have to trust their results, in the same way we trust search engines when we make searches in Internet. This is because commercial APIs can be seen as a black box – we do not know where the data comes from and how it has been treated. But, at least, we can measure its quality, as we will do next. So, we will see that –at this point– commercial APIs offer better results than other solutions. That is why damegender gives the possibility to include data from them. It is possible to download

[4] https://www.fsf.org/news/rms-addresses-the-free-software-community

Service / Tool − >	Gender API	gender-guesser	genderize.io	NameAPI	NamSor	damegender
Database size	431M	45K	114M	1M	4G	57K
Regular data updates	Yes	no	No	Yes	Yes	Yes
Unstructured full name strings	Yes	No	No	Yes	No	Yes
Surnames	Yes	No	No	Yes	Yes	Yes
Non-Latin alphabets	Partial	No	Partial	Yes	Yes	No
Implicit geo-localization	Yes	No	No	Yes	Yes	No
Exists locale	Yes	Yes	Yes	Yes	Yes	Yes
Assignment type	P	B	P	P	P	P
Free parameters	T,P	G	P,C	T	S	T,C
Prediction	No	No	No	No	No	Yes
Free license	No	Yes	No	No	No	Yes
REST API	Yes	No	Yes	Yes	Yes	Planned
Limits number of requests	Yes (200)	∞	Yes	Yes	Yes	∞
Subscription (100K requests/month)	79	0	7	150	80	0

Table 1: Comparison of the different features that name-to-gender inference services and tools offer. Assignment type = {P: Probabilistic; B: Binary}. Free Parameters = {T: total_names; P: probability; C: count; G: gender; T: trust; S: scale }. The subscription price is given in euro.

JSON files from the main commercial name-to-gender inference API solutions (e.g., genderapi, genderize, namsor, nameapi) and use it as the dataset. There are certain uses that are currently only available in such tools.

8 Feature comparison with other tools

Standard commercial name-to-gender inference APIs usually guess the gender for a single name or a list of names (from a CSV file or an API call). To express geolocalization the user can also give surnames, a country ISO code, or specify a language. Generally, you can give a probability and a counter associated to a name and gender in a certain population.

The features observed in this framework are: (i) database size (as of January 2018), (ii) if there are regular data updates, (iii) if they handle unstructured full name strings, (iv) if they handle surnames, (v) if they handle non-Latin alphabets, (vi) if implicit geolocalization is available, (vii) if locale exists, (viii) the type of assignment, (ix) if free parameters are possible, (x) if they offer prediction, (xi) if the tool is released under an open source license, (xii) if they offer an API, (xiii) the amount of monthly free requests, and (xiv) the monthly subscription cost (calculated for 100,000 requests/month)).

We have used this comparison framework and have updated it to the current situation and extended it with damegender. Results can be found in Table 1. As it can be observed, commercial services have the advantage of owning large datasets, in the order of millions or even of billions of entries. The most advanced ones offer support for non-Latin alphabets. However, they limit the amount of free requests that can be performed and their costs range from 7 euro to 150 euro per month.

API	Acc	Prec	F1	Recall
Genderapi	0.969	0.972	0.964	1.0
Genderize	0.927	0.976	0.966	1.0
Damegender (SVC)[5]	0.879	0.972	0.972	1.0
Namsor	0.867	0.973	0.924	1.0
Nameapi	0.830	0.974	0.905	1.0
Gender Guesser	0.774	0.985	0.872	1.0

Table 2: Comparison of measures of the quality of the results for the tools under study.

9 Reproducing values of accuracy and confusion matrix

In this section, we will analyze the quality of the service of existing name-to-gender inference services and tools. There are different ways to express the probability of a successful identification (e.g., confidence, scale, accuracy, precision, and recall). We can also inspect the confusion matrix to understand where the tools and services succeed or fail, and to analyze the different errors measures (error coded, error coded without not applicable values, error gender bias, not applicable coded) that can happen.

In their dataset, gender is classified as male, female, or unknown. We have used this dataset, not considering the unknown variable, for our experiments.

The results, using common information retrieval metrics, can be seen in Table 2. Accuracy is the ratio of correctly predicted observation to the total observations. It should be noted that *Accuracy* can be a misleading metric for imbalanced data sets. This is because for a sample with 85 negative and 15 positive values, classifying all values as negative would give an accuracy score of 0.85. In those cases, it is better to report other measures, such as the balanced accuracy, which normalizes true positive and true negative predictions by the number of positive and negative samples. As Santamaría and Mihaljević's data does not come from the IT domain, we can use accuracy in our research. Precision is the fraction of relevant instances

APIs	gender	male	female	undef
Genderapi	male	3589	155	67
	female	211	1734	23
Damegender	male	3663	147	0
	female	551	1497	0
Genderguesser	male	3326	139	346
	female	78	1686	204
Namsor	male	3325	139	346
	female	78	1686	204
Genderize	male	3157	242	412
	female	75	1742	151
Nameapi	male	2627	674	507
	female	667	1061	240

Table 3: Confusion matrix tables by APIs

among the retrieved instances. Recall is the fraction of the total amount of relevant instances that were actually retrieved. In our case, we have left no name out, so recall is 1 for all tools. Precision and recall are sometimes used together in the F1 Score (or f-measure) to provide a single measurement for a system. As can be observed, `Genderapi` and `Genderize` obtain the best results – although all solutions are close and reach results better than 0.8 for accuracy, except for `Gender Guesser`. `damegender` offers relatively good results. Given, however, that its focus is mainly to be used in the IT domain, where the gender is highly imbalanced, we are very positive about its precision, as accuracy is not that relevant as noted above.

We have performed a comparison using a confusion matrix for the software/tools under study (see Table 3). The most important tools (`Namsor`, `Genderapi`, and `Genderize`) improve the values of accuracy with respect to the previous comparison. In particular, `Genderapi` improves the results for *undefined*. For `Genderize`, we obtain exactly the same results. For `Genderguesser`, however, we obtain different results, which is to some extent not expected, because the software has not been modified for several years. `Nameapi`'s results is changing from male to female with more errors. In `Namsor`, the results are similar. `damegender` is not guessing undefined because we predict with machine learning (using an SVC algorithm) if the string is not in the database.

In Table 4 we can see the different measures for errors in the APIs. *Error coded* defines if the true is different than the guessed one. *Error coded without na* defines if the true is different than the guessed one, but without undefined results. *Error gender bias* allows to understand if the error is bigger for guessing males than females or viceversa. The *weighted error* defines if the true value is different than the guessed one, but giving a weight to the guessed as undefined. The most relevant information is a high index of errors for `Nameapi` and `Namsor`, while `GenderApi` and `damegender` have a low index of errors.

10 Machine Learning

10.1 Comparing ML algorithms

Table 5 shows the accuracy measures for some Machine Learning algorithms used in our guessing. The best results are given by Support Vector Machines and Random Forest – with those algorithms `damegender` achieves values that are close to more mature, proprietary solutions. It should be noted that as a result of using machine learning techniques, our classifier is binary (male and female), so no *unknown* is given as output.

10.2 Experimenting with some features

We have developed some additional experimental functionality that allows to analyze our database according to some features using machine learning algorithms. To test our approach, we have selected some features of names, such as a being the first letter, a (or o) being the last letter, contains the letter a, first letter is a vowel, last letter is a vowel, last letter is a consonant, or last letter is a. The selection of the features was verified with Principal Component Analysis. The datasets used in this experiment were the ones from the National Institute of Statistics (Spain, Uruguay, United Kingdom, United States of America, Australia and Canada). The most relevant results for the different datasets used are offered in Table 6.

As expected, countries that share language offer similar results, i.e., the variation of the chosen features between males and females is comparable. This is the case for Uruguay and Spain (Spanish), and USA and UK and Australia (English). In Canada, a country that has an ample French-speaking community these features show a different trend.

For instance, the feature *containing the letter a in the name* varies 0.2 from males to females for USA and Uruguay, and 0.1 from males to females for United Kingdom, Australia, and Spain. The feature *the last letter is an a* varies 0.5 from males to females for Australia and Spain, around 0.4 for USA and United Kingdom and 0.2 in Uruguay. The feature *the last letter is an o* varies 0.2 in (Spain, Australia) from females to males and is equal in Uruguay, USA, United Kingdom. For the feature *the last letter is a consonant* all countries give as a result that males do have it more frequently, with results that range from 0.3 to 0.5: Uruguay and USA (0.5), United Kingdom (0.4), Australia and Spain (0.3). So, the feature *the last letter is a vowel* is, as expected, the reverse of the feature *the last letter is a consonant.* The features *the first letter is a consonant* or *the first letter is a vowel* are, however, non-significant as they offer similar results in English and Spanish.

API	error	error w/o na	na coded	error gender bias
Damegender (SVC)[1]	0.121	0.121	0.0	-0.07
GenderApi	0.167	0.167	0.0	-0.167
Gender Guesser	0.225	0.027	0.204	0.003
Genderize	0.276	0.261	0.0204	-0.0084
Namsor	0.332	0.262	0.095	0.01
Nameapi	0.361	0.267	0.129	0.001

Table 4: APIs and Errors

ML Algorithm	Acc	Prec	F1	Recall
Support Vector Machines	0.879	0.972	0.972	1.0
Random Forest	0.862	0.902	0.902	1.0
NLTK (Bayes)	0.862	0.902	0.902	1.0
Multinomial Naive Bayes	0.782	0.791	0.791	1.0
Tree	0.764	0.821	0.796	1.0
Stoch. Gradient Distrib.	0.709	0.943	0.815	1.0
Gaussian Naive Bayes	0.709	0.968	0.887	1.0
Bernoulli Naive Bayes	0.699	0.965	0.816	1.0

Table 5: Machine Learning Algorithms and accuracy measures

We have done this experiment with the NLTK and INE.es datasets, with the values of accuracy reaching up to 0.745. So it makes sense to expect better results in random datasets if we add new languages and countries. However, our solution is not providing Arabic or Chinese alphabets, yet. The results of this experiment could be used to provide a good solution for nicknames, diminutives, or similar.

11 Limitations and further research

The market of gender detection tools and services is currently dominated by companies based on payment services through Application Programming Interfaces. Without doubt, they offer good results, with high accuracy values. However, their inner working cannot be studied (i.e., they work as a black-box for the outsider) and the fees that have to be paid for using their service are sometimes out of the reach of many researchers. That is why we propose a new tool, called `damegender`, with the aim of having open data of name-to-gender inference, which offers more flexibility and where researchers can build on top of it. This tool is offered under a free software license and is available on GitHub for download and enhancement. As we have shown in this paper, although still incipient, the tool offers good accuracy values based on the use of public databases from government bodies and on the use of machine learning algorithms. Nonetheless, we have to note that `damegender` is still under development, and that it has to be applied to several real repositories to confirm its benefits and address its limitations (such as a small database size of gendered names).

In addition, we have shown a glimpse of how several features of the names could be used to guess the gender if we do not have the real name, but nicknames or diminutives, a situation that is very common in free software development-supporting tools, such as IRC channels. This experiment is at this point very preliminary, and we would like to work more on it.

All in all, we hope the `damegender` tool can become a cornerstone for the scientific advancement of the study of gender (including gender gap) and diversity in the IT, and in particular in the free software community. We have therefore many hopes in linking the output of repositories like the ones that can be fetched by Perceval (git, mbox mailing lists, Gerrit, Bugzilla, etc.). As a result, we envision a free and international dataset with support for all languages and cultures.

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Dataset	contains a	last is a	last is o	last is consonant	last is vowel	1st is consonant	1st is vowel
Uruguay (F)	0.816	0.456	0.007	0.287	0.712	0.823	0.177
Uruguay (M)	0.643	0.249	0.062	0.766	0.234	0.771	0.228
Spain (F)	0.922	0.588	0.030	0.271	0.728	0.772	0.228
Spain (M)	0.818	0.030	0.268	0.569	0.430	0.763	0.236
UK (F)	0.825	0.374	0.013	0.322	0.674	0.765	0.235
UK (M)	0.716	0.036	0.039	0.780	0.218	0.799	0.200
USA (F)	0.816	0.456	0.007	0.287	0.712	0.823	0.177
USA (M)	0.643	0.020	0.061	0.765	0.234	0.840	0.159
Canada (F)	0.659	0.189	0.005	0.591	0.408	0.838	0.160
Canada (M)	0.752	0.220	0.025	0.540	0.456	0.818	0.181
Australia (F)	0.922	0.588	0.033	0.272	0.728	0.772	0.228
Australia (M)	0.818	0.030	0.269	0.570	0.430	0.763	0.237

Table 6: Informative features for different countries. F stands for females, and M for males.

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