[Artifact Presentation] Damegender: Writing and Comparing Gender Detection Tools

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Abstract

Diversity in software development teams have been identified as one of the main ingredients of a more productive, more healthy software community. Thus, the interest of the research community in identifying who is contributing has increased in the last years. In the software domain, and although other types of diversity exist, this is especially important for the case of gender. Given the large amount of publicly available data on the software development process that can be retrieved and analyzed from the Internet (e.g., GitHub, StackOverflow), the importance of having methods and tools that help with large amounts of data would be desirable. In this paper we present a free software tool, called `damegender`, which we have conceived to given a name outputs the gender and a probability. `damegender` is based on open databases from official census and uses Machine Learning to guess strings not classified as names, such as diminutives or nicknames. We have compared `damegender` with other tools, obtaining good results.

1 Introduction

In recent times, many research investigations have been made on gender diversity in the IT domain.

Examples of these efforts range from participation in Twitter [BHKZ11, MLA+11], in Wikipedia [AYCN11, HS13], in science [HSFH18, DG99], and more specifically in the software domain in StackOverflow [VCS12], GitHub [VPR+15] and in Free/Libre/Open Source Software development [RARS+14].

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

There are different ways to detect gender from a person name and perhaps a surname. A first, more rudimentary, is based on data extracted from the census, 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, about their possibilities and limitations. Therefore, (i) we evaluate the quality and price of different commercial solutions; (ii) we discuss about solutions using free licenses; (iii) we investigate what happens with those names without census, for example, nicknames or diminutives; and (iv) we elaborate on how massive gender detection from Internet, for example, mailing lists or software repositories, can be done.

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 tools has been compared with APIs using an international dataset with good results.

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

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(iv) a proof-of-concept of `damegender` to detect gender in mailing lists and software repositories.

A summary of current features of `damegender` are:

- To deduce the gender about a name in Spanish or English (current status) from open census in local.
- To decide about males and females in strings using different machine learning algorithms.
- To use the main solutions in gender detection (genderize, genderapi, namsor, nameapi and gender guesser) from a command.
- To research about why a name is related to males or females with statistics. We provide Python commands about study and compare gender solutions with: confusion matrix, accuracies, error measures. And to decide about features: statistical feature weight, principal component analysis, ...
- To determine gender gap in free software repositories or mailing lists (proof of concept).

The remainder of this paper is structured as follows: In Section 2, we explain Damegender as solution to the problem. Section 3 explains that we are using Open Datasets extracted from the states as base of truth. Section 4, presents a feature comparison with other tools. Section 5, reproduces accuracies and confusion matrix with a scientific dataset. The section 6 is about how we are using Machine Learning in Damegender. The section 7 is about conclusion, limitations and futher research.

2 Damegender

`damegender`[1] is a gender detection tool under a Free Software license (in particular, the GNU General Public License v3.0). It has been implemented in Python to take advantage of many other free software tools used in the scientific domain, such as the Natural Language Toolkit (NLTK) for Natural Language Processing [LB02], Scikit for Machine Learning [PVG+11], Numpy for Numerical Computation [VDWCV11], and Matplotlib to visualize results [Hun07]. At its current point it is linked to Perceval [DCRGB18], a tool specialized in retrieving and gathering data from software repositories, such as git and mailing lists.

The software is using an oriented to objects design with unit testing for classes and methods using nose and unit testing for Python commands using Bash. `damegender` is a Python package that can be installed using PIP (the package installer for Python) from the console.

The main reason for developing `damegender` is that there are not many free software tools that help in the identification of gender. Before `damegender`, only `Gender guesser`[2] offered a free software solution in this field [Kra06], and the project has not been active for more than three years now. The best contribution of `Gender guesser` is the dataset containing 48,528 names with a good classification by countries[3].

3 Datasets

Gender guesser 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 a 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, from institutions such as INE.es (the Spanish National Statistics Institute), or the governments of Uruguay, USA and United Kingdom. The datasets provided by the software package is incrementing the speed retrieving data.

Some Open Datasets, such the one offered by INE.es or the government of the United States of America offer support for surnames and how they are related to ethnicity. In particular, the dataset from the government of the United States of America 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.

Hence, we are using the census approach as base of truth to distinguish if a name is male or female in a geographical area. Generally, a name has a strong weight to determine if it is a male or a female on this way. 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. However, many countries do not provide Open Data census about gender and names.

[1] https://github.com/davidam/damegender

[2] https://github.com/lead-ratings/gender-guesser

[3] `https://raw.githubusercontent.com/lead-ratings/gender-guesser/master/gender_guesser/data/nam_dict.txt`

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

The third approach is based on the trust on commercial solutions, in the same way we trust search engines when we make searches in Internet. This is because commercial APIs can be seen just a black box, so we do not know where the data comes from and how it has been treated. As at this point, commercial APIs offer better results as other solutions, `damegender` gives the possibility to include data from them. Thus, it is possible to download JSON files from the main commercial gender guesser API solutions (e.g., `genderapi`, `genderize`, `namsor`, `nameapi`) and use it as the dataset. There are certain uses that are currenly only available in such tools.

As a final goal, we envision to build a free dataset with names and gender, that builds on top of `Gender Guesser` and that can be made available as Wikidata. Perhaps, to complete this work, we need to combine an automated with a manual process as described in [SM18].

Gregorio ▷ *Estaria bien contar con "the monthly subscription cost (calculated for 100,000 requests/month)" en la tabla, porque dara ms info muy relevante.* ◁ Si te da tiempo por mi adelante

4 Feature comparison with other tools

Standard commercial Application Programming Interfaces (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.

Santamaria and Mihaljevic [SM18] offers a framework to classify gender tools. 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 extended it with other tools, including `damegender` and updated it to today. Results can be found in Table 1.

5 Reproducing accuracies and confusion matrix

There are different ways to express the probability of a successful identification (e.g., confidence, scale, accuracy, precision, recall). We se the confusion matrix to understand where the different tools suceed or fail, and to analyze the different errors measures (error coded, error coded without not applicable values, error gender bias, not applicable coded) that appear.

Santamaria and Mihaljevic [SM18] explains different ways to determine gender from a name by humans and offers 7,000 names applying these methods. In their dataset, gender is classified as male, female or unknown. We have used this dataset, not considering the unknow variable, for our experiments. The results can be seen in Table 2. As can be observed, Genderapi and Genderize are obtaining the best results, although all solutions reach results better than 0.8, except for `Gender Guesser`.

Gregorio ▷ *Deberiamos explicar que es cada una de las metricas. Y tambien por que tenemos 1.0 de recall en todos los casos.* ◁ Esto es un poco largo de explicar. Est explicado de una manera abreviada ms arriba. Si te ves con energas para explicarlo, est explicado en https://easychair.org/publications/preprint/vthL

We have performed a comparison using a confusion matrix for the software/tools (see Table 3). Compared to the results obtained in [SM18], we can see that they are very similar. The most important tools (`Namsor`, `Genderapi` and `Genderize`) are improving the accuracies with respect the previous comparison. In particular, `Genderapi` has similar results, but it improves the results for *undefined*. In `Genderguesser` we obtain different results, which is to some extent not expected, because the software has not modified for several years. For `Genderize`, we obtain the same results. `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 (SVC) if the string is not in the database.

In Table 4 we can observe the different measures for errors in the APIs. The most visible conclusion is an high index of errors in `Nameapi` and `Namsor` and a low index of errors in `GenderApi` and `damegender`.

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
Assingment 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	∞

Table 1: Comparison of the different features that gender guesser software 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 }.

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)[4]	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: Different accuracies measures

APIs	gender	male	female	undef
Genderapi	male	3589	155	67
	female	211	1734	23
Damegender	male	3663	147	0
(SVC)[1]	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

6 Machine Learning

We have developed a script infofeatures.py with our datasets to analyze data about features. The datasets used in this experiment was retrieved from official datasets from national statistical institutions in Spain, Uruguay, United Kingdom, USA. The features used are: first letter, last letter, [a-z], vocals, consonants, first letter, first letter vocal, last letter vocal, last letter consonant, last letter a. The choosing of features was verified with Principal Component Analysis. The most relevant results for the different datasets are offered in Table 5.

The countries where the main language is Spanish (Uruguay + Spain) and English (USA + United Kingdom + Australia) where is having very similar variation with the features chosen between males and females with these datasets (remember that these datasets are being extracted from official statistics provided by the states). In Canada, a country French centric has different rules with this features.

The letter a is varying 0.2 from males to females in (USA and Uruguay) and 0.1 from males to females (United Kingdom, Australia and Spain). The last letter a is varying 0.5 from males to females in (Australia, Spain) around 0.4 in (USA, United Kingdom) and 0.2 in Uruguay. The last letter o from females to males is varying 0.2 in (Spain, Australia) and is equal in (Uruguay, USA, United Kingdom). For the last letter consonant all countries is giving the result that is for males, with results from 0.2 to 0.5: Uruguay and USA (0.5), United Kingdom (0.4), Australia and Spain (0.3). So last letter vocal is reverse than last letter consonant. First letter consonant or first letter vocal is a non significant feature due to so similar results in English and Spanish. The relevant metrics with the different algorithms are shown in Table 6.

The results in Table 6 show that using algorithms as Support Vector Machines or Random Forest against a scientific dataset created by independent researchers where it is possible to reach results similar to another commercial solutions about gender detection tools. Our classifier is binary (only male and female).

We were doing this experiment with NLTK and INE datasets with accuracies reaching accuracies until 0.745. So it makes sense expect better results in random datasets augmenting languages and countries. However, our solution is not providing Arabic or Chinese alphabets, yet.

So, it is possible to infer that `damegender` provides a good solution for nicknames, diminutives, or similar.

7 Limitations and further research

In some studies, for example, about Twitter or GitHub, some people can choose between different ways to detect gender (not only names). So, we can find gender detection tools from faces in images [RPC17], from hand written annotations [LSB11], or from speeches [KAS02].

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

Dataset	a	last a	last o	last consonant	last vocal	1st consonant	1st vocal
Uruguay (F) [5]	0.816	0.456	0.007	0.287	0.712	0.823	0.177
Uruguay (M) [3]	0.643	0.249	0.062	0.766	0.234	0.771	0.228
Spain (F) [3]	0.922	0.588	0.03	0.271	0.728	0.772	0.228
Spain (M) [3]	0.818	0.03	0.268	0.569	0.43	0.763	0.236
UK (F) [3]	0.825	0.374	0.013	0.322	0.674	0.765	0.235
UK (M) [3]	0.716	0.036	0.039	0.78	0.218	0.799	0.2
USA (F) [3]	0.816	0.456	0.007	0.287	0.712	0.823	0.177
USA (M) [3]	0.643	0.02	0.061	0.765	0.234	0.84	0.159

Table 5: Informative Features in Different Countries

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 Navie 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 6: Machine Learning Algorithms and accuracies measures

The market of gender detection tools is dominated by companies based on payment services through Application Programming Interfaces with good results. This market could be modified due to Free Software tools and Open Data giving more explicative results for the user.

Although machine learning techniques are not new in this field, we are giving an approach to guess strings not found in a dataset that currently is classified as unknown and the humans trend to think in gender terms many strings calling it as nicknames or diminutives.

These previous advances in computer science could be giving support to study the gender gap in repositories and mailing lists. Another future work is to create a free and universal dataset with support for all languages and cultures.

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