Un modelo de análisis estilométrico de correos electrónicos para la redacción personalizada basada en el destinatario
A model for stylometric analysis of e-mails for recipient-based personalised writing

Trabajo de Fin de Grado
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A mi hermano Luis, por enseñarme los valores (personales) que toda fórmula debe tener siempre

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Resumen

Un modelo de análisis estilométrico de correos electrónicos para la redacción personalizada basada en el destinatario

Un resumen en castellano de media página, incluyendo el título en castellano. A continuación, se escribirá una lista de no más de 10 palabras clave.

Palabras clave

Máximo 10 palabras clave separadas por comas

Abstract

A model for stylometric analysis of e-mails for recipient-based personalised writing

An abstract in English, half a page long, including the title in English. Below, a list with no more than 10 keywords.

Keywords

10 keywords max., separated by commas.

Contents

List of figures

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List of Algorithms

Chapter 1

Introduction

"Have you ever retired a human by mistake?"
— Rachael - Blade Runner (1982)

Smartphone development meant not only a technological advance but a social revolution too. This intelligent telephones have brought with them countless paradigm shifts in terms of the social sphere. Since then, we are able to speak of a new model of human relationship both between people and with our technology. This current relation standard is due to the easy and quick way of accessing the different information that our mobile devices provide us. Long waits (nowadays the meaning of "long" waits has changed too, people consider more than two or three second too much time) for obtaining anything such as accessing to a website or showing any operation result, are excessively tedious and could be even frustrating for some smartphone users. When we are using our mobile, we want, as fast as possible, the information we are looking for. Precisely because of this, Human-Computer Interaction (HCI) becomes a very important part in the process of development of most applications, not only in terms of speed of response and efficiency of algorithms, but also in how we show different information and the easiness for obtaining it.

As for the relationships between people, as we have said, they have dramatically changed. There is no doubt that the main driving technologies behind this transformation of our relational paradigm are the social networks and the instant messaging. Focusing on the latter, it is necessary to make a breakdown of what consequences to our interpersonal interaction the instant communication have brought with itself. Just as it happens with the HCI, easiness and speed are probably the first features we look for when we are going to send or receive any information to anybody. If we also expect a reply, the ideal would be to obtain it as quickly as possible. Therefore, in most of occasions, in practice we are looking for an "automatic" response from a human, what practically implies that everyone is "obligated" to be connected at any time with the answer we are asking for prepared. This new insight into the relationships between people, that perceives the humans as servers who send a request waiting for a quickly reply with the expected data, has promoted a very fast sending of short messages which intends to substitute and simulate an spoken conversation. These little texts are often concise and summarised, and they form an atomic semantic unit, namely they have their own independent meaning.

1.1. Incentive

Introducción al tema del TFM.

1.2. Objectives

Descripción de los objetivos del trabajo.

1.3. Working plan

Aquí se describe el plan de trabajo a seguir para la consecución de los objetivos descritos en el apartado anterior.

1.4. Explicaciones adicionales sobre el uso de esta plantilla

Si quieres cambiar el **estilo del título** de los capítulos, edita `TeXiS\TeXiS_pream.tex` y comenta la línea `\usepackage[Lenny]{fncychap}` para dejar el estilo básico de LaTeX.

Si no te gusta que no haya **espacios entre párrafos** y quieres dejar un pequeño espacio en blanco, no metas saltos de línea (\\) al final de los párrafos. En su lugar, busca el comando `\setlength{\parskip}{0.2ex}` en `TeXiS\TeXiS_pream.tex` y aumenta el valor de $0.2ex$ a, por ejemplo, $1ex$.

TFMTeXiS se ha elaborado a partir de la plantilla de TeXiS[1], creada por Marco Antonio y Pedro Pablo Gómez Martín para escribir su tesis doctoral. Para explicaciones más extensas y detalladas sobre cómo usar esta plantilla, recomendamos la lectura del documento `TeXiS-Manual-1.0.pdf` que acompaña a esta plantilla.

El siguiente texto se genera con el comando `\lipsum[2-20]` que viene a continuación en el fichero .tex. El único propósito es mostrar el aspecto de las páginas usando esta plantilla. Quita este comando y, si quieres, comenta o elimina el paquete *lipsum* al final de `TeXiS\TeXiS_pream.tex`

1.4.1. Texto de prueba

[1] `http://gaia.fdi.ucm.es/research/texis/`

Chapter 2

State of the Art

"Who controls the past controls the future.
Who controls the present controls the past."
— 1984 - George Orwell (1949)

In order to be able to develop a model for stylometric analysis of e-mails for recipient-based personalised writing, the first thing we need to understand is the fundamentals of this communication method. For this reason, in Section 2.1, we will delve into both the protocols that define it and the specific structure of the Gmail service, since the e-mail account that we will analyse and that will be used to design the model around the data extracted from it belongs to that service.

Once we have laid the foundations of communication through e-mail and, specifically, the Gmail service, we will study how to analyse the wording of the different messages, that is, we will learn the concepts of the field of study known as stylometry (see Section 2.2). Specifically, we will also present the research related to e-mails and the most common techniques and metrics used for various purposes.

Finally, for the modelling of a recipient-based custom writing system, we will need to understand the functioning of a very popular technique in information retrieval called Latent Semantic Indexing. For this reason, in section 2.3, we will explain this method in detail, which will be used in later chapters.

2.1. Electronic Mail

Electronic Mail (Guide, 2005, Chapter 11) is a communication service which has been used since 1971 (Ibrahim et al., 2018) when the first network e-mail with the text "QWERTYUIOP" was sent through ARPAnet (Advanced Research Projects Agency Network, the first network which implements the TCP/IP protocol) with the experimental protocol CYPNET. Nowadays, the messages are delivered by using a client/server architecture. In this way, an e-mail is created by using a client-side mail program. Then, this software sends the message to a server, which will redirect it to the recipient's mail server. From there, the e-mail is delivered to the addressee.

In order to make all this process possible, an Internet standard that extends the format of e-mail messages, and a wide range of network protocols exist for allowing different machines (which often execute distinct operative systems and make use of different mail programs) to share e-mails. In this section, we are going to study this standard, these protocols and the API which is going to be used for reading, sending e-mails and accessing

to the user's e-mail data. First of all, we are going to explain the MIME standard (see Section 2.1.1) which specifies the format of e-mail messages. Then we are going to explain the main e-mail management protocols, both electronic mail transmission protocol (such as Simple Mail Transfer Protocol, which is explained in Section 2.1.2) and message access protocol (such as Post Office Protocol and Internet Message Access Protocol, which are studied in Sections 2.1.3 and 2.1.4, respectively).

In spite of being a mail server-independent solution, as we will see, we are going to find security issues which are going to hinder our user's e-mail data access. These trials come from the automatic server access. For this reason, Gmail API is going to be introduced (see Section 2.1.5) and, finally, the assessment of the advantages and disadvantages of making use of the e-mail protocols or the Gmail API is discussed (see Section 2.1.6).

2.1.1. MIME

To be able to automatically create messages and read the body of the e-mails, it is essential to understand what the MIME standard consists in. Hence, in this section we are going to give a general idea about this.

MIME, whose acronym stands for Multipurpose Internet Mail Extensions, is an Internet standard for the exchange of several file types (text, audio and video among others) which provides support to text with characters other than ASCII, non-text attachments, body messages with numerous parts (known as multi-part messages) and headers information with characters other than ASCII. It is defined in a series of Request For Comments (RFC): RFC 2045 (Freed and Borenstein, 1996b), RFC 2046 (Freed and Borenstein, 1996c), RFC 2047 (Moore, 1996), RFC 2049 (Freed and Borenstein, 1996a), RFC 2077 (Nelson and Parks, 1997), RFC 4288 (Freed and Klensin, 2005a) and RFC 4289 (Freed and Klensin, 2005b).

Virtually all e-mails written by people on the Internet and a considerable proportion of these automatically generated messages are transmitted in MIME format via SMTP (see Section 2.1.2). Internet e-mail messages are so closely associated with SMTP and MIME that they are usually called SMTP/MIME messages.

The content types defined by the MIME standard are of great importance also outside the context of e-mails. Examples of this are some network protocols such as HTTP from the Web. HTTP requires data to be transmitted in an e-mail-type message context although the data may not be an e-mail itself.

Nowadays, no e-mail program or Internet browser can be considered complete if it does not accept MIME in its various facets (text and file formats).

In this section we will learn about the MIME type nomenclature (see Section 2.1.1.1), which is necessary for being able to exchange several file types. Then, we will illustrate the MIME structure of an e-mail, consisting of MIME headers (see Section 2.1.1.2) and, finally, two common MIME message encoding (base64 and quoted-printable) are explained (see Sections 2.1.1.3 and 2.1.1.4, respectively).

2.1.1.1. Type Nomenclature

Each data type has a different name in MIME. These names follow the format: type-/subtype (both type and subtype are strings), in such a way that the first denotes the general data category and the second the specific type of that information. The values the type can take are:

- *text*: means that the content is simple text. Subtypes like *html*, *xml* and *plain* can

follow this type.

- *multipart*: indicates that the message has numerous parts with independent data. Subtypes like *form-data* and *digest* can follow this type.
- *message*: it is used to encapsulate an existing message, for example when we want to reply a e-mail and add the previous message. Subtypes like *partial* and *rfc822* can follow this type.
- *image*: means that the content is an image. Subtypes like *png*, *jpeg* and *gif* can follow this type.
- *audio*: indicates that the content is an audio. Subtypes like *mp3* and *32kadpcm* can follow this type.
- *video*: denotes that the content is an video. Subtypes like *mpeg* and *avi* can follow this type.
- *application*: it is used for application data that could be binary. Subtypes like *json* and *pdf* can follow this type.
- *font*: means that the content is a file which defines a font format. Subtypes like *woff* and *ttf* can follow this type.

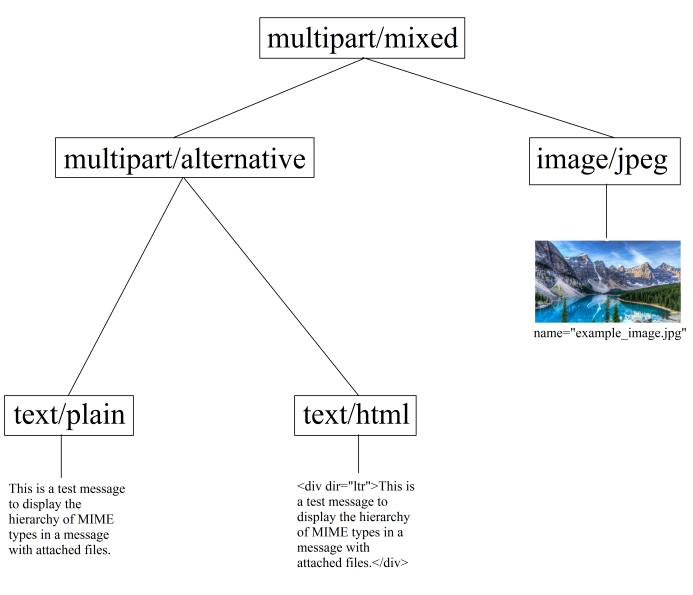
2.1.1.2. MIME headers

MIME has several headers which appear in all e-mails sent with this standard. The most important of them are the following:

- *Content-Type*: the value of this header is the type and subtype of the message with the same structure that we have explained before. For example, if we have the header *Content-Type: text/plain*, it means that the message is a plain text. The use of the type *multipart* makes the creation of messages with parts and subparts organized in a tree structure (in which leaf nodes can belong to any type and the rest of them can belong to any multipart subtype variety) possible (Freed and Borenstein, 1992, Section 7.2). A feasible composition of a message with a part with plain text and other non-text parts could be constructed by using *multipart/mixed* as the root node like in Figure 2.1. Indeed, in the example of Figure 2.1 we can observe the use of *multipart/alternative* for a message which contains the body both in plain text and in html text. Other different e-mails constructions are possible (like forwarding with the original message attached by using *multipart/mixed* with a *text/plain* part and a *message/rfc822* part) thanks to the tree structure of the *Content-type* header.

  Another important detail, that we can observe in the example in Figure 2.1, is the fact that each node of the tree structure of the e-mails is visited and showed following the pre-order traversal.

- *Content-Disposition*: this header is used to indicate the presentation style of the part of the message. There are two ways to show the part: *inline* content-disposition (which means that the content must be displayed at the same time as the message) and *attachment* content-disposition (the part is not displayed at the same time as the message and it requires some form or action from the user to see it). Furthermore, this header also provides several fields for specifying other type of information about



MIME-Version: 1.0
From: Sender <sender@gmail.com>
Date: Fri, 4 Oct 2019 22:06:29 +0200
Message-ID: <CADkvQ12BgJJxjqApD6AcNcAhJJEZ5FBkPi-9Pw__XduXgN_3sQ@mail.gmail.com>
Subject: Example MIME message
To: addressee@gmail.com
Cc: addressee2@gmail.com
Content-Type: multipart/mixed; boundary="000000000000abadb805941b3c9d"

--000000000000abadb805941b3c9d
Content-Type: multipart/alternative; boundary="000000000000abadb605941b3c9b"

--000000000000abadb605941b3c9b
Content-Type: text/plain; charset="UTF-8"
Content-Transfer-Encoding: quoted-printable

This is a test message to display the hierarchy of MIME types in a message
with attached files.

--000000000000abadb605941b3c9b
Content-Type: text/html; charset="UTF-8"
Content-Transfer-Encoding: quoted-printable

This is a test message to display the hierarchy of MIME types in a message with attached files.

--000000000000abadb605941b3c9b--
--000000000000abadb805941b3c9d
Content-Type: image/jpeg; name="example_image.jpg"
Content-Disposition: attachment; filename="example_image.jpg"
Content-Transfer-Encoding: base64
Content-ID: <16d985155126855b6e01>
X-Attachment-Id: 16d985155126855b6e01

--000000000000abadb805941b3c9d--

Figure 2.1: MIME types tree structure of an e-mail example

the content, such as the name of the file and the creation or modification date. The following example is taken from RFC 2183 (Troost et al., 1997) and, as we will explain after the example, it does not match with the syntax of this same header in the example that we can see in the last part of the example message of Figure 2.1:

```
Content-Disposition: attachment; filename=genome.jpeg;
modification-date="Wed, 12 Feb 1997 16:29:51 -0500";
```

As we have said, this syntax is different from the one used in the e-mail example of Figure 2.1. This results from the fact that, in HTTP, the header we find in that figure (*Content-Disposition: attachment*) is usually used for instructing the client to show the response body as a downloadable file. As we can observe, it has a *filename* field which is used for establishing the default file name when the user is going to download it.

- *Content-Transfer-Encoding*: when we want to send some files in a message, sometimes they are represented as 8-bit character or binary data, which are not allowed in some protocols. On this account, it is necessary to have a standard that indicates how we should re-encode such data into a 7-bit short-line format. The Content-Transfer-Encoding header (Freed and Borenstein, 1992, Section 5) will tell the client which transformation has been used for being able to transport that data. Therefore, and for lack of a previous standard which states a single Content-Transfer-Encoding mechanism, the possible values which specify the type of encoding are: *'base64'* (see Section 2.1.1.3), *'quoted-printable'* (see Section 2.1.1.4), *'8bit'*, *'7bit'*, *'binary'* and *'x-token'*. All these values are not case sensitive. If this header does not exist, we can assume that the value of this header is *'7bit'*, which means that the body of the message is already in a seven-bit mail-ready representation, in other words, all the body of the message is represented as short lines of US-ASCII data. Despite *'8bit'*, *'7bit'* and *'binary'* indicate that the content has not been transformed, they are useful for knowing the kind of encoding that the data has. This header will generally be omitted when the Content-Type has the *multipart* or *message* type (as it happens

in the message example of Figure 2.1), because it also admits the last three types we have mentioned.

It is common to add another header (as we can see in Figure 2.1) called *charset*, the value of which represents the original encoding of data so the client is able to decode it.

2.1.1.3. Base64 encoding

As we have studied when we learnt how the MIME headers (see Section 2.1.1.2) are, we can find e-mail whose content encoding is base64. Base64 (Josefsson, 2006) is a group of reversible binary-to-text encoding schemes which represent binary data as a sequence of ASCII printable characters. It makes use of a radix-64 to translate each character, because 64 is the highest power of two than can be represented using only printable ASCII characters. Indeed all the Base64 variants (like base64url) utilise the characters range A-Z, a-z and 0-9 in that order for the first 62 digits, but the chosen symbol for the last two digits are very different between them. In particular, the MIME (see Section 2.1.1) specification, established in RFC 2045 (Freed and Borenstein, 1996b), describes base64 based on Privacy-enhanced Electronic Mail (PEM) protocol (defined by Linn (1993), Kent (1993), Balenson (1993) and Kaliski (1993)), which means that the last two characters are '+' and '/', and the symbol '=' is used for output padding suffix. In the same way, MIME does not stablish a fixed size for the base64 encoded lines, by contrast it specifies a maximum size of 76 characters.

If we try to apply standard base64 in a URL encoder, it will translate the characters '+' and '/' to its hexadecimal representation ('+' = '%2B' and '/' = '%2F'). This will cause a conflict in heterogeneous systems or if we use it in data base storage, because of the character '%' produced by the encoder (it is a special symbol of ANSI SQL). This is why modified Base64 for URL variants exists (such as base64url in Josefsson (2006)), where the '=' character has no usefulness and the '+' and '/' symbols are replaced by '-' and '_' respectively. Besides it has no impact on the size of encoded lines.

2.1.1.4. Quoted-printable enconding

Other reversible binary-to-text encoding that could be used in the content of a MIME message is the quoted-printable encoding (Borenstein and Freed, 1993). Making use of printable characters (such as alphanumeric and '=') proved capable of transmitting 8 bit data over a 7 bit protocol. Unlike base64, if the original message is mostly composed of ASCII characters, the encoded text is readable and compact.

Each byte can be represented via two hexadecimal characters. On this basis, the '=' symbol followed by two hexadecimal digits are enough to encode all the characters except the printable ASCII ones and the end of line. For example, if we want to represent the 12^th ASCII character we can encode it as '=0C' or if the equality symbol (whose decimal value is 61) is in our original message, it could be encoded as '=3D' (note that despite being a printable ASCII character it must be encoded as it is a special character in this encoding). This is how quoted-printable encodes the different characters.

In respect of the maximum line size, as it happens with the MIME specification of the base64 (see Section 2.1.1.3), it has a length of 76 characters each encoded line. To achieve this goal and still be able to decode the text getting the original message, quoted-printable adds *soft line breaks* at the end of the line consisting of the '=' symbol and it does not modify the encoded text.

2.1.2. Simple Mail Transfer Protocol

Simple Mail Transfer Protocol (also known as SMTP) is a network connection-oriented communication protocol used for the exchange of e-mail messages. It was originally defined by Postel (1982) (for the transfer) and by Crocker (1982) (for the message). It is currently defined by Klensin (2008) and Resnick (2008). However, this protocol has some limitations when it comes to receiving messages on the destination server. For this reason, this task is intended for other protocols such as the Internet Message Access Protocol (see Section 2.1.4) or the Post Office Protocol (refer to Section 2.1.3), and SMTP is used specifically to send messages.

Making use of SMTP, an e-mail is "pushed" from one mail server to another (next-hop mail server) until it reaches its destination. The message is not routed according to the message recipients specified during the client's connection to the SMTP server, but from the destination mail server. Thanks to the fact that this protocol has a feature to initiate mail queue processing, an intermittently connected mail server can extract messages from another remote server when necessary.

2.1.3. Post Office Protocol

Post Office Protocol (also known as POP) is an application protocol (in OSI Model) for obtaining e-mails stored in a remote Internet server called POP server. It was originally defined by Reynolds (1984) (it was POP version 1, also known as POP1). Current POP version (POP3, in general when we talk about POP we refer to this version) is detailed by Myers et al. (1996).

POP3 was designed for receiving e-mails. Using POP3, users with intermittent or very slow Internet connections (such as modem connections) can download their e-mail while online and check it later even when offline. The general operation is: a client using POP3 connects, gets all messages, stores them on the user's computer as new messages, deletes them from the server, and finally disconnects. However some mail clients include the option to leave messages on the server. They use the order UIDL (Unique IDentification Listing) which, unlike most POP3 commands, does not identify messages depending on their mail server ordinal number. This results from the fact that the mail server ordinal number creates problems when a client tries to leave messages on the server, since messages with numbers change from one connection to the server to another. Accordingly, a server which makes use of UIDL, assigns a unique and permanent character string to each message. Thus, when a POP3-compatible mail client connects to the server, it uses the UIDL command to map the message identifier. This way the client can use that mapping to determine which messages to download and which to save at the time of downloading.

Like other old Internet protocols, POP3 used a signature mechanism without encryption. The transmission of POP3 passwords in plain text still occurs. Nowadays POP3 has various authentication methods that offer a diverse range of levels of protection against illegal access to users' mailboxes.

The advantage over other protocols is that between server-client you do not have to send so many commands for communication between them. The POP protocol also works properly if you do not use a constant connection to the Internet or to the network that contains the mail server.

2.1.4. Internet Message Access Protocol

Internet Message Access Protocol (also known as IMAP) is an application protocol, designed as an alternative to Post Office Protocol (see Section 2.1.3) in 1986, which allows the access to stored messages in an Internet server. As with the Post Office Protocol, with IMAP you can access your e-mail from any computer with an Internet connection. The current version of IMAP (IMAP version 4 review 1, or IMAP4rev1) is defined by Crispin (2003).

In contrast to Post Office Protocol, IMAP allows multiple clients to manage the same mailbox. This fact results from the main differences between these two protocols: IMAP does not remove e-mail from the server until the client specifically requests it (as POP removes them by default, it is impossible to access them from another device which has not downloaded the messages) and it does not download the messages to the user's computer (clients may optionally store a local copy of them). This last property gives raise to several advantages with regard to Post Office Protocol: the immediate notification of the arrival of a mail (due to it works in permanent connection mode) while POP checks if there are new e-mails every few minutes (which causes an appreciable rise in traffic and in the time the user has to wait to send a request to the server, because it is necessary to complete the download of all new messages first), it is possible to create shared folders with other users (it depends on the mail server), the e-mails do not take up memory in the user's local device while POP downloads them regardless of whether they are going to be read or not (effectively IMAP has to download a message when it is going to be read, but they are temporary files and only the e-mail headers are downloaded to manage the mailbox) and it allows the user to manage folders, templates and drafts in server in addition to be able to search a mail from keywords.

2.1.5. Gmail API

Gmail is a free e-mail service developed by the company Google. Users can access Gmail on the web itself and through third-party programs that synchronize e-mail content via POP or IMAP protocols. It also has a mobile application to manage the user's e-mail. Gmail began as a limited beta version on April 1, 2004 and completed its testing phase on July 7, 2009. As stated by BBC news (3rd July 2018): "Gmail is the world's most popular e-mail service with 1.4 billion users".

As we will see in Section 2.1.6, due to the automatic server access, directly using the communication protocol for electronic mail transmission (SMTP) and for retrieving e-mail messages from a mail server (POP or IMAP) will cause us security problems in accessing the user's e-mail data. For this reason, we are going to make use of Gmail API, that we will study in this Section. Thus, in Section 2.1.5.1 we are going to study the necessary protocol for accessing the Gmail API and consequently for being able to get into the user's e-mail data. Further on, we will require a resource (like a programming object) we can work with and represent all the Gmail structure (see Section 2.1.5.2). Once we count on this general resource, we have the necessary tools to be able to understand and handle the internal architecture of the Gmail API and the different means it provides in order to achieve our goal. Therefore, in Sections 2.1.5.3 to 2.1.5.6 we are going to delve into the essential resources for our purpose: labels, messages, threads and drafts.

Finally, as this API is not the only means of accessing the user's mail data (we have studied other ways in previous sections), we will end with a brief description about the API usage limits (in Section 2.1.5.7) to assess its use with respect to other methods of e-mail access.

2.1.5.1. OAuth 2.0 Protocol

Open Authorization or OAuth (Cook and Messina, 2019a) is an open standard which allows simple authorization flows for web services or applications. It is a protocol defined in Hardt (2012) which allows the site's users to share their information with another site without providing their full identity. This mechanism is used by companies like Google, Facebook, Twitter and Microsoft to allow users to share information about their accounts with third-party applications or websites.

Gmail API, as it also happens in the case of other Google APIs, uses OAuth 2.0 protocol (Google, 2019f) to handle authentication and authorization. It will provide us a secure and trusted login system to access the user's Gmail data.

The basic working process of OAuth 2.0 protocol can bee seen in Figure 2.2. As we can observe, at first our application carries out a request in which it sends a token. This token includes, among other things, a credential, which helps Google Servers to identify the application, and a list of OAuth 2.0 Scopes (Google, 2019e), which are a "mechanism in OAuth 2.0 to limit an application's access to a user's account. An application can request one or more scopes. This information is then presented to the user in a consent screen, and the access token issued to the application will be limited to the scopes granted" (Cook and Messina, 2019c). We will use the Gmail API OAuth 2.0 Scope which allows us to read, compose, send, and delete e-mails.

Once the user has logged in the Gmail account (authentication) and accepted all the necessary permissions that our application needs (authorization), our process receives an authorization code which is going to be exchanged for an access token (Cook and Messina, 2019b). Then, we will be in possession of the OAuth 2.0 credentials for the user (Google, 2019d) which we are going to use for accessing the user's Gmail account.

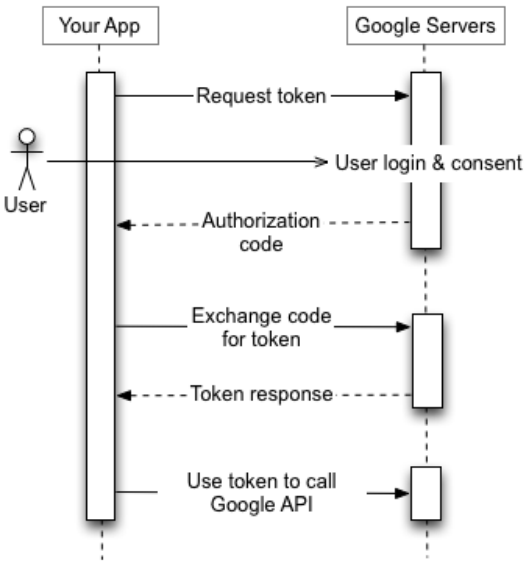


Figure 2.2: OAuth 2.0 for Web Server Applications and Installed Applications. Image extracted from Google (2019f)

2.1.5.2. Users resource

At this point, with the OAuth 2.0 credentials, we are able to call the Gmail API. For this purpose, it is necessary to construct a resource (Google, 2019a, /v1/reference) for interacting with the API. As we will see later, this resource will lead us to manage e-mails, drafts, threads and everything we will like to do with the user's Gmail data.

By using the OAuth 2.0 credentials, we are able to get in contact with the Google Servers and request what is known as users resource (Google, 2019a, /v1/reference/users), which holds all the necessary resources for our task, such as labels (see Section 2.1.5.3), messages (see Section 2.1.5.4), threads (see Section 2.1.5.5) and drafts (see Section 2.1.5.6). In practice, the users resource has instance methods which get in contact with Google Servers and return these other Gmail API resources that we are going to need (the methods' names are *labels()*, *messages()*, *threads()* and *drafts()*, respectively). Now, in next sections, we are going to explain all the resources we can create with the user resource.

2.1.5.3. Labels resource

As we have seen in the explanation of the users resource (Section 2.1.5.2), we can obtain the labels resource (Google, 2019a, /v1/reference/users/labels) by invoking *labels()* instance method of our users resource. It manages the entire set of our e-mail labels, which categorize messages and threads within the user's mailbox.

Labels resource is an object which allows us to access to the different e-mail labels of the user, such as *INBOX*, *UNREAD* and *SENT*. With the labels resource methods, we can obtain each of these "user's labels" which have a dictionary structure and their representation is what we can observe hereunder:

```
{
    'id' : string, # The immutable identifier of the label
    'name' : string, # The display name
    # The visibility of messages in the Gmail web interface
    'messageListVisibility' : string,
    'labelListVisibility' : string, # The visibility of label
    # The owner type of the label ('system' or 'user')
    'type' : string,
    # Total number of messages with the label
    'messagesTotal' : integer,
    # Number of unread messages with the label
    'messagesUnread' : integer,
    # Total number of threads with the label
    'threadsTotal' : integer,
    # Number of unread threads with the label
    'threadsUnread' : integer,
    'color' : {
       # Text color of the label, represented as hex string
       'textColor' : string,
       # Background color represented as hex string #RRGGBB
       'backgroundColor' : string
    }
}
```

The important fields we are going to need are the *name*, the *type* and the number of total messages and threads with the label (which are *messagesTotal* and *threadsTotal* fields, respectively). Labels with *system* type, such as *INBOX*, *SENT*, *DRAFTS* and *UNREAD*, are internally created and cannot be added, modified or deleted.

2.1.5.4. Messages resource

In most of the operations we are going to execute, the correct management of messages will be essential. Therefore, knowing how the e-mails are represented in Gmail API and how to use them is imperative to understand how to work with this API. For this reason, in this section we are going to delve into the messages resource (Google, 2019a, /v1/reference/users/messages) of the Gmail API. As we saw in Section 2.1.5.2, we can access to this resource by invoking the *messages()* instance method when we have a users resource.

As with the labels resource, the messages resource manages the set of all messages of the user's e-mail. With the messages resource methods, we can obtain each of these "user's messages" which, regardless of which programming language is used, have a dictionary structure and their representation is what we can see down below:

```
{
    'id' : string,
    'threadId' : string,
    'labelIds' : [ string ],
    'snippet' : string,
    'historyId' : unsigned long,
    'internalDate' : long,
    'payload' : {
        'partId' : string,
        'mimeType' : string,
        'filename' : string,
        'headers' : [
        {
            'name' : string,
            'value' : string
        }
        ],
        'body' : {
            'attachmentId' : string,
            'size' : integer,
            'data' : bytes
        },
        'parts' : [ (MessagePart) ]
    },
    'sizeEstimate' : integer,
    'raw' : bytes
}
```

The more important keys of this data structure for this work are:

- *id*: an immutable string which identifies the message.
- *threadId*: we will explain the thread resource in Section 2.1.5.5 and we will see that a thread is composed of different messages that share common characteristics. The value of this field is a string which represent the identifier of the thread the message belongs to.
- *labelIds*: a list of the identifiers of labels (see Section 2.1.5.3) applied to the message.
- *payload*: as we can see in the resource representation above, it has a dictionary data structure. The *payload* field is the parsed e-mail structure in the message parts. The more important keys of the *payload* field are:

- *mimeType*: the MIME type (see the explanation of *Content-Type* header in Section 2.1.1.2) of the message part.
- *headers*: a list of headers. It contains the standard RFC 2822 (Resnick, 2001) e-mail headers such as *To*, *From*, *Subject* and *Date*. Each header has a *name* field, which is the name of the header (for example *From*), and a *value* field, which is the value of the header (following the same example as with the *name* field, *example@gmail.com* could be the value).
- *parts*: a list which contains the different MIME message child parts (we have gone into it in depth in the Section 2.1.1).
- *body*: a dictionary structure which contains the body data of this part (see Section 2.1.1) in case it does not contain MIME message parts (otherwise it will be empty). This structure should not be confused with an attached file. Each MIME part contains a body property regardless of MIME type of the part.

- *raw*: the entire e-mail message in an RFC 2822 (Resnick, 2001) formatted and base64url (see Section 2.1.1.3) encoded string.

2.1.5.5. Threads resource

When we access to our inbox, we are actually seeing the inbox threads instead of the messages resource. Every message, even if it is an only e-mail without a reply, is enclosed in a thread resource (Google, 2019a, /v1/reference/users/threads) which is essentially a list, perhaps unitary, of messages resources. In fact, as we can observe in the following resource representation, each thread (which can be obtained thanks to the threads resource due to it manages the entire set of threads of a user's e-mail), in its dictionary structure, has a list of messages resources:

```
{
    'id' : string, # The identifier of the thread
    'snippet' : string, # A short part of the text
    'historyId' : unsigned long,
    'messages' : [ users.messages resource ]
}
```

2.1.5.6. Drafts resource

The last Gmail API resource we will study is the most easy to understand after knowing all the structures related with e-mails that we have explained in the above sections: the drafts resource (Google, 2019a, /v1/reference/users/drafts). Its representation is very simple:

```
{
    'id' : string # The immutable identifier of the draft
    'message' : users.messages resource
}
```

As we can observe, a draft is virtually a messages resource with an identifier. Indeed, in order to create a new draft with the *DRAFT* label we must create a MIME message (see Section 2.1.1) as we have to do when we want to send a new e-mail by using the *send* messages resource method.

2.1.5.7. API Usage Limits

One factor to be taken into account is the limitations of the Gmail API (Google, 2019a, /v1/reference/quota) which could become a drawback in the application development. It has a limit on the daily usage and on the per-user rate. In order to measure the usage rate, "quota units" are defined depending on the method invoked (main methods of each resource are explained in Section 3.1). In Table 2.1 we can consult the value of some methods in quota units (we have selected the most important methods for our purpose, for the quota units of other methods it is recommended to refer to (Google, 2019a, /v1/reference/quota)).

Method	Where the method is explained	Quota units
getProfile	3.1.3	1
labels.get	3.1.4	1
messages.get	3.1.5	5
messages.list	3.1.5	5
messages.send	3.1.5	100
threads.get	3.1.6	10
threads.list	3.1.6	10
drafts.create	(Google, 2019a, /v1/reference/users/drafts)	10

Table 2.1: Main methods' quota units

However, both daily usage limit and per-user rate limit are acceptable for the type of software we want to build: 1,000,000,000 quota units per day and 250 quota units per user per second. Therefore there are no constraints (for our purpose) that avoid us to use this API.

2.1.6. Advantages and disadvantages of e-mail protocols versus the use of Gmail API

Without using the Gmail API, we may be able to access mail accounts by implementing the different e-mail protocols that we have studied. Indeed, this implementation would allow us to access them regardless of the mail server. In other words, we would be able to work with any e-mail account without the need of being a Gmail one. However, when we try to develop an application which is going to access to a user's e-mail account, Google Servers detect it as a non-authorised login and block the authentication process. Then they send to the user a warning titled "A login attempt has been blocked" with the following information: "*Someone just used your password to try to sign in to your account from a non-Google application. Although Google has blocked access, you should find out what happened. Check your account activity and make sure that only you have access to your account*".

Against this background, it is possible to change the user's security settings for allowing the automatic accessing to the account. However, it is not recommended (due to possible security issues) and creates a sense of insecurity for the user of the application that requires this configuration.

On the other hand we have the Gmail API, which facilitates the access to e-mail's data. Besides, its only disadvantage is to limit the daily usage of this technology by imposing quota units. However, this quota units are enough for achieving our aim. For these reasons, and because of the e-mail accounts that we will study belongs to Gmail, the Gmail API has been chosen as the most suitable way for managing the user's e-mail account.

2.2. Computational stylometry

This field of Artificial Intelligence (related with Natural Language Processing and Natural Language Generation) is in charge of studying the writing style in natural language written documents (although it is often used in applications like the detection of plagiarism in programmes). In this section we are going to delve into it in order to know the state of art of this field of study. To achieve this, first a brief introduction is presented (see Section 2.2.1), and then the different applications and techniques used in Computational stylometry are explained (see Section 2.2.2). In addition, it will be necessary to explain the presentation of computational stylometry in the specific field of e-mails (see Section 2.2.3) since, as we can deduce, they present singularities with respect to other types of documents. Finally, various style writing metrics are going to be explained (see Section 2.2.4) for the purpose of calculating and studying them in the extracted dataset (the entire set of e-mails that have been extracted).

2.2.1. Introduction to Computational Stylometry

Stylometry (Hughes et al., 2012) is the application of the study of linguistic style to written language, although it has also been successfully applied to music (both in composition such as in the researches of Manaris et al. (2005), Casey et al. (2008) and Huron (1991); and performances, such as the study carried out by Sapp (2008)) and visual arts (Taylor et al., 1999; Hughes et al., 2010). It could be defined as the linguistic discipline that applies statistical analysis to literature in order to evaluate the author's style through various quantitative criteria.

Stylometry is characterized by the assumption that there are implicit features in the texts that the author introduces unconsciously, such as the use of a specific vocabulary that makes up the writer's mental lexicon, the lexical-syntactic structure of the sentences in the document, etc (Burrows, 1992).

According to Holmes (1998), stylometry was born in 1851 when Augustus de Morgan, an English logician, hypothesized that the problem of authorship could be addressed by determining whether one text "does not deal in longer words" (De Morgan and De Morgan, 1882) than another. Following this idea, three decades later, the American physicist Thomas Mendenhall carried out research in which he measured the length of several hundred thousand words from the works of Bacon, Marlowe and Shakespeare (Mendenhall, 1887). However, its results showed that word length is not an effective writing style feature which allows us to discriminate between different authors. Since then, numerous investigations have been carried out to analyse the parameters that define writing style more precisely.

Tweedie et al. (1996) define the writing style as "a set of measurable patterns which may be unique to an author". For this reason, various machine learning and statistical techniques have been used to discover the characteristics that determine it. One of the first and most famous successes was the resolution of the controversial authorship of twelve of the Federalist Papers. These documents, a total of eighty-five papers, were published anonymously in 1787 to convince the citizens of New York State to ratify the constitution. They are known to have been written by Alexander Hamilton, John Jay and James Madison, who subsequently claimed their contributions from each of them. However, twelve were claimed by both Madison and Hamilton. By using the frequency of occurrence of function words, previously used by Ellegard (1962), and employing numerical probabilities adjusted by Bayes' theorem, Mosteller and Wallace (1964) attribute the twelve papers dis-

puted to James Madison. Thereafter, Federalist Papers is a famous example in this area for testing the different solutions, for example Tweedie et al. (1996) make use of neural networks to solve this problem.

2.2.2. Applications and techniques

In addition to the detection and verification of authorship in historical, literary and even forensic investigations, stylometry is used in other areas such as the detection of fraud and plagiarism, the classification of documents according to their genre or audience, etc. Other possible applications of this area are the prediction of the gender, age or personality of the author as Schwartz et al. (2013) studied; inference of the date of composition of texts, which is known as "stylochronometry" (Stamou, 2007; Juola, 2007); and even natural language generation with style (Gatt and Krahmer, 2018, Section 5.1).

To address all these problems, statistical techniques are mostly used. Some of them belong to the field of machine learning such as Neural Networks (Ng et al., 1997), Support Vector Machines (Abbasi and Chen, 2005), Principal Components Analysis (Binongo and Smith, 1999), Decision Trees (Apte et al., 1998), Adaboost (Cheng et al., 2011), K-Nearest Neighbors (Kucukyilmaz et al., 2008) and Naive Bayes (Sahami et al., 1998). Others are based on purely statistical approaches (such as cusum in Summers (1999) or Thisted and Efron (1987)) or merely syntactic-statistical concepts as in the well-known software implementations such as stylo (Eder et al., 2016) and STYLENE (Daelemans et al., 2017). To this last type also belong techniques based on dictionary word counting using Linguistic Inquiry and Word Count also known as LIWC (Pennebaker et al., 2015), while more recent ones which use simple lexico-syntactic patterns, such as n-grams and part-of-speech (POS) tags (Mihalcea and Strapparava, 2009; Ott et al., 2011), belong to the machine learning approach. We can also find techniques outside this paradigm, such as the writing style features driven from Context Free Grammar (CFG), as we can observe in the research of Feng et al. (2012), genetic algorithms (Holmes and Forsyth, 1995) and Markov chains (Tweedie and Baayen, 1998).

2.2.3. Style in e-mails

Electronic mails are a very specific type of document in stylometry. Their length, usually quite short, and the level of reliability, in most occasions between the informality of spoken word and the relative formality of an official letter, are two of their characteristic that make them so peculiar. For this reason, a lot of researchers have focused their attention on these type of texts, taking special interest the identification pertaining to the authorship of e-mail messages such as the published thesis by Corney (2003) or Thomson and Murachver (2001), which have investigated the existence of gender-preferential language styles in e-mail communications.

Despite being able to use most of the techniques mentioned above, both the machine learning (such as K-Nearest Neighbors used by Calix et al. (2008) or Support Vector Machines used by De Vel et al. (2001)) and the purely statistical approaches (such as regression algorithms used by Iqbal et al. (2010) for analysing 292 different features in order to verify the e-mail authorship), it is possible to find big differences with other documents such as structural features that pure text lacks. The usage of greeting text, farewell text and the inclusion of a signature are three examples of these structural features that we must take into account.

Due to that e-mail documents have several features which distinguish them from longer formal text documents (such as literary works or published articles), they make any com-

putational stylometry problem challenging compared with others. First of all, as we have previously said, the length of the e-mails is much shorter than other documents, which results in certain language-based metrics not being appropriate (such as *hapax legomena* or *hapax dislegomena*, that is to say, the number or ratio of words used once or twice, respectively). This e-mail's feature also makes contents profiling based on traditional text document analysis techniques, such as the "bag-of-words" representation (for example when Naive Bayes approach is being used) more difficult.

Other electronic mail's particularity is the composition style used in formulating them. That is, an author profile derived from normal text documents (for example published articles) can not be the same as that obtained from a common e-mail document (De Vel et al., 2001). For example, the briefness of the e-mails causes a greater tendency to get to the point without excessive detours on the subject, in other words, they have a concise nature. We may also find that they contain a greater number of grammatical errors or even a quick compositional style that is more similar to an oral interaction, as these can become a dialogue between two or more interlocutors. In this way, the authoring composition style and interactivity features attributed to electronic mails shares some elements of both formal writing and speech.

The main feature of e-mail against other types of documents that we are interested in is the variation in the individual style of e-mail messages due to the fact that they, as an informal and fast-paced medium, exhibit variations in an individual's writing styles due to the adaptation to distinct contexts or correspondents (Argamon et al., 2003). Many authors such as Allen (1974) and De Vel et al. (2001) support the hypothesis that each writer has certain unconscious habits when writing an e-mail that depend on the target audience. However, to the best of our knowledge, there is no research that uses stylometry to set the parameters of writing style according to the recipient of the message.

2.2.4. Style metrics

According to Rudman (1997), at least a thousand stylistic features have been proposed in stylometric research. However, there is no agreement among researchers regarding which "style markers" yield the best results. Chen et al. (2011) (150 stylistic features were extracted from e-mail messages for authorship verification), Gruner and Naven (2005) (sixty-two stylometric measurements applied to pairs of text were calculated and then analysed in order to detect plagiarism in text documents) and Canales et al. (2011) (82 stylistic features extracted from sample exam documents were analysed using a K-Nearest Neighbours classifier for the purpose of authenticating online test takers) are only three examples of a large list of researches which look for appropriate writing style metrics to carry out their work.

As Brocardo et al. (2013) indicate, analysing a huge number of features does not necessarily provide the best results, as some features provide very little or no predictive information. And, as Brocardo et al. (2013) do, our approach is to build on previous works by identifying and keeping only the most discriminating features.

According to Abbasi and Chen (2008) existing stylistic features can be categorised as lexical (word, or character-based statistical measures of lexical variation), syntactic (including function words, punctuation and part-of-speech tag n-grams), structural (especially useful for online text, include attributes relating to text organization and layout), content-specific (are comprised of important keywords and phrases on certain topics) and idiosyncratic (include misspellings, grammatical mistakes, and other usage anomalies) style markers. However, this is not the only existing classification. There are many others like

the one proposed by Corney et al. (2001), in which we see how features are divided as character-based, word-based, document-based, function word frequency distribution and word length frequency distribution; or the one proposed by Feng et al. (2012) which use a more simple classification of features in words, shallow syntax and deep syntax. However, hereafter, we are going to use the classification explained in Abbasi and Chen (2008) for referring to the different metrics.

In a vast majority of approaches, stylometrists rely on high-frequency items. Such features are typically extracted in level of (groups of) words, characters or part of speech, called n-grams (Kjell et al., 1994). Whereas token level features have longer tradition in the field, character n-grams have been borrowed from the field of language identification in Computer Science (Stamatatos, 2009; Eder, 2011). However, the most reliably successful features have been function words (short structure-determining words: common adverbs, auxiliary verbs, conjunctions, determiners, numbers, prepositions and pronouns) and word or part of speech n-grams.

A number of successful experiments with function words have been reported, such as Craig (1999), Koppel et al. (2006) and De Vel et al. (2001). N-grams (word or part of speech ones) to some extent overlap with function words, since frequent short words count higher, but their frequencies also take into account some punctuation and other structural properties of the text. Besides, due to n-gram features are noise tolerant and effective, and e-mails are non-structured documents, many researches working with this specific type of texts, as Brocardo et al. (2013) and Corney et al. (2001), have used them.

Most reports, such as the previously mentioned composed by Kjell et al. (1994) and Corney et al. (2001), indicate that 2 or 3-grams gave good categorisation results for different text chunk sizes but these results were thought to be due to an inherent bias of some n-grams towards content rather than style alone. The effectiveness of n-grams comes from the fact that they are a successful summary marker, which can replace other markers. It is able to capture characteristics about the author's favourite vocabulary, known as word n-grams (Diederich et al., 2003) and are a content-specific feature, as well as sentence structure, known as part of speech n-grams (Baayen et al., 1996; Argamon et al., 1998), which are a syntactic feature. The problem can be found with a small corpus, since, as Baayen et al. (2000) suggest, even successful style markers may not be representative for differentiating gender, theme, author, etc. in these cases.

Another metric based on the frequency of the items is the Probabilistic Context Free Grammar (PCFG) which is used by Feng et al. (2012) in order to detect deception.

All the techniques for setting the parameters of writing style presented so far in this section have a higher level of complexity than others. This may be due to a high level of memory required during calculations (as is the case with n-grams) or a higher algorithmic complexity (as in the case of PCFG). We can also find other simple popular metrics used in other research. A good example is the lexical feature of Burrow's Delta (Burrows, 2002), which is an intuitive distance metric which has attracted a good share of attention in the community, also from a theoretical point of view (Argamon, 2008; Hoover, 2004b,a). Another example is the lexical feature of type-token ratio, which is given by the formula $R = V/N$, where N is the number of units (word occurrences) which form the sample text (tokens) and V is the number of lexical units which form the vocabulary in the sample (types). The behaviour of this style marker was studied in Kjetsaa (1979) and an approximation to Normal distribution of types per 500 tokens in all text analysed was found. Certainly it would seem that the type-token ratio would only be useful in comparative investigations where the value of N is fixed.

In order to study the sentence structure, as part of speech n-grams do, there are many

other style markers such as the syntactic feature given by calculating the percentage of part of speech (POS) tags (which have been used in many previous studies in stylometry, such as Argamon-Engelson et al. (1998), Zhao and Zobel (2007), Ott et al. (2011) and Feng et al. (2012)) and the proportion of stop words in a text proposed in Ril Gil et al. (2014). One possible approach consists in the style features which take into account the part of speech tags. The verb-adjective ratio and the article-pronoun ratio belong to this category. The first was proposed in Antosch (1969) and significant results were obtained by showing that this measure is dependent on the theme of the work. For example, folk tales have higher values and scientific works have lower values. The second was studied by Brainerd (1974), where there is evidence of a connection between the number of articles and the number of pronouns in a text.

It is also possible to extract conclusions about the sentence structure through the punctuation features (which belong to the syntactic metrics category), as Baayen et al. (2002) studied. One possibility of metrics is to calculate the amount of commas, periods, semi-colons, ellipsis and brackets as Calix et al. (2008) did.

As we have studied in Section 2.1.1.2, some e-mails use HTML formatting. With this information, De Vel et al. (2001) includes the set of HTML tags as a structural metrics and studies the frequency distribution of them as one of their 21 structural attributes. These also include the number of attachments, position of requoted text within e-mail body, usage of greeting and/or farewell acknowledgement and the inclusion of a signature text. Other structural attributes, including technical features such as the use of various file extensions, fonts, sizes, and colours, have been used in works such as Abbasi and Chen (2005). This is another possibility for studying the sentence structure with an structural feature approach.

In addition to the structural features, De Vel et al. (2001) study other lexical-syntactic metrics based on the amount of blank lines, the total number of lines, count of hapax legomena, the total number of alphabetic, upper-case and digit characters in words and the number of space, white-space and tab spaces in the text.

As for the lexical-syntactic characteristics, we can also mention those defined in Calix et al. (2008), some of which are related to punctuation (such as based on the amount of dollar signs, ampersands, number signs, percent signs, apostrophes, asterisks, dashes, forward slashes, colons, pipe signs, mathematical signs, question and exclamation marks, at signs, backward slashes, caret signs, underscores, vertical lines, etc.), to sentence and paragraph (such as the number of sentences beginning with upper or lower case and the average number of words per paragraph) and to words (such as number of times "well" and "anyhow" appear). Other researchers such as Corney et al. (2001) (184 stylometric measurements were calculated and analysed by using a Support Vector Machine learning method in order to identify the authorship of electronic mails) make use of letter frequencies, distribution of syllables per word, hapax dislegomena, word collocations, preferred word positions, prepositional phrase structure and phrasal composition grammar. As regards frequency distributions of syllables per word, Fucks and Lauter (1965) discovered that it discriminated different languages more than specific authors. However, in Brainerd (1974), it is claimed that a model based on a translated negative binomial distribution was a better fit to such distributions than Fucks and Lauter (1965) translated Poisson distribution. Lastly, Brainerd (1974) concludes that some authors styles are more homogeneous than others with regard to syllable count and it would appear that the distribution of syllables per word in a corpus, being an easily accessible index of its style, is one area that may prove profitable in stylometry studies.

The most famous and ancient (as we have seen in Section 2.2.1) lexical feature is

the word length (it is also applied to each part of speech as it is explained by Allen (1974)). However, as Smith (1983) concludes: "Mendenhall's method now appears to be so unreliable that any serious student of authorship should discard it". Besides, it is too strongly influenced by the language used or the subject matter dealt with and, furthermore, cannot always admit enough variance to be significant. A better way to measure style based on this criterion is to construct a graph to show what percentage of words in the text have one letter, two letters, three, and so on up to the length of the longest word; but the influence of the language itself on such measurements cannot be denied (Williams, 1970).

A variation of the word length is the sentence length. It was proposed in Yule (1939) and its major advantage is that there is a much wider range of words per sentence than letters per word. However, the major disadvantage is that it can be easily controlled by an author and it requires more text than is needed for measuring average word lengths.

Other very popular lexical features are those which measure the diversity of a text (such as the Simpson's Index, presented in Simpson (1949), or entropy, used in Holmes (1985)), the richness of its vocabulary (such as the Yule's Characteristic, defined in Yule (2014), and the definition of richness proposed by Honoré (1979)) and the level of difficulty, such as the proposed in Dale and Chall (1948), the Gunning Fog Index (Gunning, 1968) or the Flesch-Kincaid index (DuBay, 2004).

As for the content-specific features, the most popular metric, a part from the word n-gram, is known as the "bag of words", which consists of storing how many times each word appears. Previous work, such as Mihalcea and Strapparava (2009) and Ott et al. (2011), has shown that "bag of words" are effective in detecting features in different documents. As Allen (1974) claims: "each writer tends to keep relatively constant the distribution of high frequency determiners, such as articles and conjunctions, whose information content is small compared to that of nouns and verbs. The other end of a frequency list is also of use in that sometimes a distinguishing stylistic feature is the avoidance of certain words".

Finally, in respect of idiosyncratic features, they include misspellings, grammatical mistakes, and other usage anomalies (Abbasi and Chen, 2008). Such features are extracted using spelling and grammar checking tools and dictionaries (Chaski, 2001). Idiosyncrasies may also reflect deliberate author choices or cultural differences, such as use of the word "center" versus "centre" (Koppel and Schler, 2003). Besides, we can add the study of features which determine the level of formality of the text, as it happens in Sheika and Inkpen (2012).

2.3. Latent Semantic Indexing

Latent Semantic Indexing (Deerwester et al., 1990; Dumais et al., 1995), as Hofmann (1999) defines it, "is an approach to automatic indexing and information retrieval that attempts to overcome these problems by mapping documents as well as terms to a representation in the so-called *latent semantic space*". In order to construct this (high dimensional vector) space, the Latent Semantic Indexing (LSI) makes use of two popular mathematical tools: the Terms Frequency-Inverse Document Frequency (Chowdhury, 2010) and the Singular Value Decomposition (Golub and Reinsch, 1971). These are studied in Sections 2.3.1 and 2.3.2. Thus, Latent Semantic Indexing (LSI) has the required information for being able to get the result of a query with keywords with the purpose of obtaining the most similar document. The way of getting the suitable answer is explained in Section 2.3.3.

2.3.1. Terms Frequency-Inverse Document Frequency

The Terms Frequency-Inverse Document Frequency (TF-IDF), as Tang et al. (2014) claim, is a popular weighting scheme which expresses how relevant a word is to a document in a collection. The TF-IDF value increases proportionally to the number of times a word appears in the document, but is compensated by the frequency of the word in the document collection, which allows for handling the fact that some words are generally more common than others.

Variations of the TF-IDF weighting scheme are frequently used by search engines as a fundamental tool to measure the relevance of a given document to a user's query, thus establishing an order or ranking of the document. TF-IDF can be successfully used for filtering so-called stop-words (words that are used in almost all documents), in different fields such as spam detection (Sasaki and Shinnou, 2005).

TF-IDF is the product of two measurements, Term Frequency (TF) and Inverse Document Frequency (IDF). There are several ways to determine the value of both. In the case of Term Frequency (Jones, 1972), the easiest way of calculating $tf(t,d)$ (that is to say the TF value of the term t in document d) is counting the total number of times a term appears in an document (an e-mail in our work). Denoting the absolute frequency of the term t in document d by $f(t,d)$, other possibilities are the boolean frequencies (which returns the value of one if a term appears in the document and zero otherwise), logarithmically scaled frequency (defined by the expression $tf(t,d) = \log(1 + f(t,d))$), term frequency adjusted for document length (defined by the formula $tf(t,d) = f(t,d)/N$ where N is the number of words in d) and augmented frequency (to prevent a bias towards longer documents), which is defined by the following formula:

$$tf(t,d) = \frac{f(t,d)}{\max\{f(t,d) : t \in d\}}$$

The Term Frequency can be used without calculating the Inverse Document Frequency, such as the researchers Cohen et al. (1996) and Segal and Kephart (1999).

Inverse Document Frequency is a measure of whether or not the term is common in a document collection. It is obtained by dividing the total number of documents by the number of documents containing the term, and the logarithm of that ratio is taken:

$$idf(t,D) = \log \frac{|D|}{|\{d \in D : t \in d\}|}$$

Where D is the collection of documents. Of course there are other ways to calculate it, but this is the most common (Tang et al., 2014), used by researchers as Drucker et al. (1999). The TF-IDF is calculated as $tfidf(t,d,D) = tf(t,d) \cdot idf(t,D)$. A high TF-IDF weight is achieved with a high frequency of termination (in the given document) and a small frequency of occurrence of the term in the entire collection of documents.

Once we have calculated the TF-IDF value of all the terms of all the documents in the collection, we have the TF-IDF table, in which each row corresponds to a document and each column to a word. This term-frequency matrix could be modified using Singular Value Decomposition.

2.3.2. Singular Value Decomposition

In linear algebra, the Singular Value Decomposition (SVD) of a real or complex matrix is a factorization of the matrix with many applications in statistics and other disciplines

(Stewart, 1993). It is performed on the matrix to determine patterns in the relationships between the terms and concepts contained in the text.

If we denoted with A the transpose term-frequency matrix generated using Term Frequency-Inverse Document Frequency with m rows (which is the number of different words) and n columns (number of different documents), the SVD approximates this matrix into three other matrix: an m by r (where r is the rank of A) term-concept vector matrix T, an r by r singular values matrix S, and a n by r concept-document vector matrix D. They will satisfy the following conditions:

1. $A \approx TSD^T$
2. $T^T T = Id_r$ (Id_r is the identity matrix with r rows and columns)
3. $D^T D = Id_r$
4. $S_{1,1} \geq S_{2,2} \geq S_{3,3} \geq \ldots \geq S_{r,r} > 0$ and S is a diagonal matrix.

Thanks to the Eckart-Young-Mirsky (Stewart, 1993) theorem, it is possible to truncate the diagonal matrix S to another with a smaller rank, keeping the $k \ll r$ larger singular values, where k is typically on the order 100 to 300 dimensions. The truncation operation preserves the most important semantic information in the text while reducing noise. Then we can present the following expression:

$$A \approx A_k = T_k S_k D_k^T$$

2.3.3. LSI Querying

The main objective of LSI is to calculate the similarity between documents. A query with different keywords may be a document, that is to say, we are able to evaluate the similarity between a query and each document of the TF-IDF table.

Firstly, it is required to calculate the TF vector of the given query (as we have explained in Section 2.3.1). Once we have it, and making use of the initial TF-IDF table, it is possible to obtain the TF-IDF vector of the given query without modifying the table.

As we know the linear combination with which from the set of words we can build the k components that make up the truncated TF-IDF matrix, we are able to calculate the value of each component from the TF-IDF vector of the query. Then we can define the similarity between two vectors (the query q and any document d) as the cosine of the angle θ they form. This way if the vectors are the same, their angle is zero and its cosine one. We can calculate the cosine thanks to the expression of the dot product of two vectors: $q \cdot d = \|q\| \cdot \|d\| \cos\theta$. Taking into account that the dot product is the sum of the product of each component of the vector, we can obtain the following expression:

$$\cos(q, d) = \frac{q \cdot d}{|q| \cdot |d|} = \frac{\sum_{i=1}^{k} q_i d_i}{\sqrt{\sum_{i=1}^{k} q_i^2} \sqrt{\sum_{i=1}^{k} d_i^2}}$$

Where v_i is the i-th component of the vector v.

With this method, we can find the most similar document given a keywords query only by calculating the cosine of all the documents with the query and taking the text that has the highest value.

Chapter 3

Used technologies

"We've arranged a global civilization in which most crucial elements profoundly depend on science and technology. We have also arranged things so that almost no one understands science and technology. This is a prescription for disaster. We might get away with it for a while, but sooner or later this combustible mixture of ignorance and power is going to blow up in our faces."
— The Demon - Haunted World: Science as a Candle in the Dark
Carl Sagan (1995)

Once we have studied the state of the art, we will know the different technological tools that we will need in the implementation of our work.

As our work is focused on the texts of the e-mails, it will be necessary to study in detail the Gmail API and the functions it provides us with to carry out the different operations (see Section 3.1). Then, a syntactic analyser will be required in order to measure the style of the documents, that is to say, to be able to apply stylometric techniques. For this purpose, we have chosen spaCy (see Section 3.2). We will also need a framework to develop the different web services we will implement, a task for which we will make use of Flask (see Section 3.3). Finally, we will explain the database system that we are going to use for the storage of the different data.

3.1. How to work with Gmail API

In order to be able to read and send e-mails, it is necessary to access to the user's e-mail data. For this reason, the different ways to obtain this information were studied. One of them is the Gmail API, which allows developers to perform all the actions we need in an easy way.

Gmail API can be used in several programming languages such as Python, PHP, Go, Java, .NET, ... Due to the greater number of examples in the starting guides of the Gmail API (Google, 2019a) and the previous knowledge that was already had of it, Python (version 3.7) was chosen for the first contact with this technology.

The following tries to be a step-by-step explanation of what is necessary to know to access the user's Gmail account, create a message, send an e-mail previously created, create and update a draft, reply a received message (for this it is necessary to know how to create an e-mail) and read important information of message threads and individual e-mails (such as who is the sender, who has received the message, the subject, the date, the e-mail's body,

the attached files, ...). Different methods of Gmail API resources (explained in Section 2.1.5) are studied to achieve this aim.

As we have seen in Section 2.1.5.1, in order to work with Gmail API, it is necessary to obtain the required OAuth 2.0 credentials. For this reason, we are going to developed an implementation which gets them (see Section 3.1.1). Then, with that credentials, we are going to build a Gmail resource (see section 3.1.2), which is necessary for obtaining the rest of the resources that we have explained. Finally, in the rest of this section, we are going to delve into the methods of each resource that we already know.

3.1.1. How to obtain OAuth 2.0 credentials

As we have seen before (see Figure 2.2), to be in possession of OAuth 2.0 client credentials from the Google API Console is required for having the appropriate permissions to use the Gmail API (this credential is the first request token that is sent to the Google Servers in the OAuth 2.0 exchange of information).

The Google API Console, also known as Google Console Developer[1], built into Google Cloud Platform, makes possible an authorized access to a user's Gmail data. In order to achieve it, having a Google account is a prerequisite because accessing to this platform will be necessary. Once this web has been accessed, at first we have to create a new development project by clicking in "New Project" in the control panel (which is the main tab of the Google Console Developer and the one that opens by default when you access it). When we have already created a project, we will enable the API we are going to work with, in this case the Gmail API. To do this we will look for it in the search engine that we can find in the library of APIs of this platform. Now we can apply for the credentials we need. Accessing to the "Credentials" tab and clicking on "Create Credentials" will lead us to an easy questionnaire, about what type of credentials we prefer, that we have to answer by basing on what type of application we are building. Then we must download the .json file and save it in the folder we are going to work in.

Before starting the development of the implementation of the OAuth 2.0 protocol which will provide us a secure and trusted login system to access to the user's Gmail data, we must install the Google Client Library[2] of our choice of language (we will use Python, so we have to install the libraries *google-api-python-client*, *google-auth-httplib2* and *google-auth-oauthlib*).

There are many ways to obtain the necessary permissions for accessing to the user's e-mails data following the OAuth 2.0 protocol. As this is a first contact with the Gmail API, only with the intention of knowing the possibilities it offers to us and its advantages and disadvantages for future implementations, we are going to develop a simple script which is using a class very useful for local development and applications that are installed on a desktop operating system. The class *InstalledAppFlow*, in *google_auth_oauthlib.flow* (Google, 2019b), is a *Flow* subclass (which belongs to the same library). Thanks to this last class we have mentioned, *InstalledAppFlow* uses a *requests_oauthlib.OAuth2Session* instance at *oauth2session* to perform all of the OAuth 2.0 logic. Besides it also inherits from *Flow* the class method *from_client_secrets_file* which creates a *Flow* instance from a Google client secrets file (this file will be the .json file that we obtained through the Google API Console) and a list of OAuth 2.0 Scopes (Cook and Messina, 2019c).

After constructing an *InstalledAppFlow* by calling *from_client_secrets_file* as we have explained, we can invoke the class method *run_local_server* which instructs the user to

[1] `https://console.developers.google.com/`

[2] `https://developers.google.com/gmail/api/downloads`

open the authorization URL in the browser and will try to automatically open it. This function will start a local web server to listen for the authorization response. Once there is a reply, the authorization server will redirect the user's browser to the local web server. As we can see in Figure 2.2, the web server will get the authorization code from the response and shutdown, that code is then exchanged for a token.

In summary, it is possible to obtain the necessary permissions from the user and to follow the OAuth 2.0 protocol, by executing these instructions (written in Python):

```
from google_auth_oauthlib.flow import InstalledAppFlow

# Create a flow instance
flow = InstalledAppFlow.from_client_secrets_file('credentials.json',
['https://mail.google.com/'])
# Obtain OAuth 2.0 credentials for the user
creds = flow.run_local_server(port = 0)
```

Now, we are able to call Gmail API by using the token (which is stored in the variable *creds*). However, before starting to work on the e-mail data, we should save the OAuth 2.0 credentials since otherwise the user would need to go through the consent screen every time the application is opened. To prevent this from happening, to differentiate access from mail management and consequently to reuse as much code as possible, we have implemented the following class *auth*, in *auth.py*, with a main method *get_credentials*:

```
1  import pickle
   import os.path
   from google_auth_oauthlib.flow import InstalledAppFlow
   from google.auth.transport.requests import Request
5
   class auth:
   def __init__(self, SCOPES, CLIENT_SECRET_FILE):
   self.SCOPES = SCOPES
   self.CLIENT_SECRET_FILE = CLIENT_SECRET_FILE
10
   def get_credentials(self):
   """
   Obtains valid credentials for accessing Gmail API
   """
15 creds = None
   # The file token.pickle stores the user's access and refresh tokens
   if os.path.exists('token.pickle'):
   with open('token.pickle', 'rb') as token:
   creds = pickle.load(token)
20 # If there are no (valid) credentials available, let the user log in
   if not creds or not creds.valid:
   if creds and creds.expired and creds.refresh_token:
   creds.refresh(Request())
   else:
25 flow = InstalledAppFlow.from_client_secrets_file(
   self.CLIENT_SECRET_FILE, self.SCOPES)
   creds = flow.run_local_server(port=0)
   # Create token.pickle and save the credentials for the next run
   with open('token.pickle', 'wb') as token:
30 pickle.dump(creds, token)
   return creds
```

As we can observe in line 17 within *get_credentials* method, at first we check if the

file called *token.pickle* exists, and in that case, it is opened and its information is stored in the variable *creds*. Thus, we avoid to force the user to open the authorization screen. By contrast, as we have seen before, if it does not exists, we obtain the credentials by calling the class methods *from_client_secrets_file* and *run_local_server* (it is written between lines 25 and 30).

There is another case that is also reflected in the code above (in lines 23 and 24): the credentials are expired (it is possible to check it by executing *creds.expired*) and they can be refreshed (the OAuth 2.0 refresh token is *creds.refresh_token*) (Google, 2019d). In this situation, we will refresh the access token by invoking the method known as *refresh* and by giving it a *Request* object (Google, 2019c) from *google.auth.transport.requests* as the function parameter which used to make HTTP requests.

3.1.2. Building a Gmail Resource

At this point, with the OAuth 2.0 credentials, we are able to call the Gmail API. For this purpose, it is necessary to construct a resource (Google, 2019a, /v1/reference) for interacting with the API. The *build* method, from *googleapiclient.discovery* library (Gregorio, 2019), creates that object. As we will see later, this resource will lead us to manage e-mails, drafts, threads and everything we will like to do with the user's Gmail data. This is why, using the *auth.py* file explained in Section 3.1.1, we are going to start every user session with the instructions below (or their equivalents in the language we are using):

```
from googleapiclient.discovery import build
import auth

SCOPES = ['https://mail.google.com/']
CLIENT_SECRET_FILE = 'credentials.json'

# Creation of an auth instance
authInst = auth.auth(SCOPES, CLIENT_SECRET_FILE)
# Constructing the resource API object
service = build('gmail','v1',credentials=authInst.get_credentials())
```

Henceforth, we will use the *service* variable to relate it with the resource object created by the *build* method.

3.1.3. Users resource

The *build* method could be called for obtaining any resource of any Google API (by giving it the suitable parameters). Our specific created *service*[3] has an important instance method that we are going to invoke for every execution: the *users()* method. It returns what is known as users resource (Google, 2019a, /v1/reference/users).

The users resource has also instance methods, which return other Gmail API resources that we are going to need, such as *drafts()*, *labels()* (see Section 3.1.4), *messages()* (see Section 3.1.5) and *threads()* (see Section 3.1.6) which return drafts, labels, messages and threads resources respectively. Moreover, it possesses the three methods that we explain hereunder (we must remember that for being able to execute any method that we are going to explain in this and next sections, it is necessary to have the appropriate authorization with at least one of the required scopes that we can look up in its documentation):

[3] http://googleapis.github.io/google-api-python-client/docs/dyn/gmail_v1.html

- *getProfile(userId)*: it returns an object with a dictionary structure as it follows:

```
{
   # Total number of threads in the mailbox
   'threadsTotal' : integer,
   # User's e-mail address
   'emailAddress' : string,
   # ID of the mailbox's current history record
   'historyId' : string,
   # Total number of messages in the mailbox
   'messagesTotal' : integer
}
```

  The parameter is a string with the user's e-mail address. If we remember the authentication process, at no time we ask the user about the e-mail address because we decided to let the Google API functions to handle all that procedure. Therefore we have no way to know this information. Nevertheless, the special string value *'me'* can be used to indicate the authenticated user. For knowing the required scopes for invoking this function look up in (Google, 2019a, /v1/reference/users/getProfile).

- *stop(userId)*: stop receiving push notifications for the given user mailbox. As it happens with *getProfile*, the parameter is a string with the user's e-mail address, but it is possible to use the especial string value *'me'*.

- *whatch(userId, body)*: set up or update a push notification watch on the given user mailbox.

As we are going to call only the *getProfile* method, we have described on details this first function and we have just given an idea about what the rest of them do. Now, in next sections, we are going to explain all the resources we can create with the user resource.

3.1.4. Labels resource

As we have studied, we can obtain the mentioned labels resource (Google, 2019a, /v1/reference/users/labels) by invoking *labels()* instance method of our users resource, that is to say, by using our *service* variable, the instruction *service.users().labels()* will return the label resource.

In order to obtain a label object, we will use the methods of this resource: create, delete, get, list, patch and update. In this manner, for example, we can store a label object by calling the next instructions:

```
labels = service.users().labels()
labelList = labels.list(userId = 'me').execute()
label = labels.get(id = labelList[0]['id'], userId = 'me')
```

It is necessary to use the *get* method because, as we can look up in (Google, 2019a, /v1/reference/users/labels/list), the *list* method only contains an *id*, *name*, *messageListVisibility*, *labelListVisibility* and *type* of each label, whereas the *get* method returns the label resource with all the information.

3.1.5. Messages resource

As any other resource, the messages resource has different methods, many of whom we are going to need in this work. Therefore, being aware of these methods and the operations

that we are able to do with them is imperative for facing our goals. For this reason, in this section we are going to delve into the messages resource methods. As we saw in Section 3.1.3, we can access to this resource by invoking the *messages()* method when we have a users resource. We will limit ourselves to describing the methods we may need to use:

- *attachments()*: returns the attachments resource (for more information about this resource refer to (Google, 2019a, /v1/reference/users/messages/attachments)).
- *get(userId, id, format = 'full', metadataHeaders = None)*: if successful, this method returns the requested messages resource. Its parameters are:
  - *id*: the identifier string of the message we are looking for.
  - *userId*: the user's e-mail address. As it happens with the *getProfile* method of the users resource (see Section 3.1.3), the special string value *'me'* can be used to indicate the authenticated user.
  - *format* (optional parameter): the format in which we want the message returned. This field can take the following punctual values: *'full'* (returns the entirely e-mail data with body content parsed in the *payload* messages resource field and the *raw* field is empty), *'metadata'* (returns only an e-mail message with its identifier, e-mail headers and labels), *'minimal'* (returns only an e-mail message with its identifier and labels) and *'raw'* (returns the entirely e-mail message data with the body content in the *raw* messages resource field as a base64url (see Section 2.1.1.3) encoded string and the *payload* field is empty).
  - *metadataHeaders* (optional parameter): it is only used when the format parameter takes the punctual value of *'metadata'*. It is a string list where we have to insert the headers we want to be included.

  For knowing the required scopes for invoking this function refer to (Google, 2019a, /v1/reference/users/messages/get).
- *list(userId, includeSpamTrash = false, labelIds = None, maxResults = None, pageToken = None, q = None)*: returns a resource with the following structure:

```
{
    'messages' : [ users.messages resource ],
    'nextPageToken' : string,
    'resultSizeEstimate' : unsigned integer
}
```

  As it happens with the *list* method of the labels resource (see Section 3.1.4), *'messages'* list does not contain all of a message information (for obtaining the full e-mail data we can use *get* method). Each element of this list only contains the *id* and *threadId* field.

  The parameters of this method are:

  - *userId*: user's e-mail address (we can use the special string value *'me'*).
  - *includeSpamTrash* (optional parameter): boolean parameter which determines if it includes messages with the labels *SPAM* and *TRASH* in the result of the operation.
  - *labelIds* (optional parameter): it is a list which let us filter the messages by only returning e-mails with labels that match all of the identifiers that belong to this list.

- *maxResults* (optional parameter): an integer which determines the maximum number of messages to return.
- *pageToken* (optional parameter): string which specifies a page of results.
- *q* (optional parameter): string which let us do an specific query (with the same query format as the Gmail search box) and filter the messages by only returning e-mails that match with it.

For knowing the required scopes for invoking this function refer to (Google, 2019a, /v1/reference/users/messages/list).

- *send(userId, body = None, media_body = None, media_mime_type = None)*: it sends the given message to the e-mail addresses specified in the *To*, *Cc* and *Bcc* headers. The first two parameters are the only ones we will use. The first (*userId*) is the user's e-mail address (we can use the special string value *'me'*) and the second is the message we want to send in an RFC 2822 (Resnick, 2001) format. For knowing the required scopes for invoking this function refer to (Google, 2019a, /v1/reference/users/messages/send).

3.1.6. Threads resource

In addition to messages, we will also manage the threads of the user. Because of it, knowing the main operation with them will be necessary. The most important methods of this resource are:

- *get(userId, id, format = 'full', metadataHeaders = None)*: if successful, this method returns the requested threads resource. In respect of the parameters, they are defined in the same way as in *get* messages resource method (see Section 3.1.5) with the exception of the parameter *format*, whose only difference is that it does not accept the *'raw'* value. For knowing the required scopes for invoking this function look up in (Google, 2019a, /v1/reference/users/threads/get).

- *list(userId, includeSpamTrash = False, labelIds = None, maxResults = None, pageToken = None, q = None)*: if successful, it returns a dictionary structure analogous to the view in the *list* message resource method (see Section 3.1.5). Needless to say, instead of returning a messages resource list it will give us a threads resource list, which does not contain the complete information of each thread (for example each element of the list has not a list of messages resource). Full thread data can be fetched using the previous method. The parameters of this method are defined in the same way as the *list* messages resource method. For knowing the required scopes for invoking this function refer to (Google, 2019a, /v1/reference/users/threads/list).

3.2. spaCy

After extracting the user's e-mails, we should be able to analyse the body of the e-mails. To do this we will need a syntactic parser in order to separate the different texts in tokens (in other words, to segment text into words, punctuation marks, etc.) and obtain different characteristics from them (such as their part of speech) for the purpose of being able to calculate the metrics explained in Section 2.2.4. To attain that objective, we are going to use the library spaCy[4].

[4] `https://spacy.io/`

In this section we are going to explain the reasons why we chose spaCy (see Section 3.2.1) and its usefulness in our work (see Section 3.2.2).

3.2.1. spaCy versus others syntactic parsers

We have chosen spaCy as our syntactic parser against others for several reasons, supported by published researches (such as the one carried out by Choi et al. (2015)), that we will explain below.

SYSTEM	YEAR	LANGUAGE	ACCURACY	SPEED (WPS)
spaCy v2.x	2017	Python / Cython	**92.6**	*n/a*
spaCy v1.x	2015	Python / Cython	91.8	13,963
ClearNLP	2015	Java	91.7	10,271
CoreNLP	2015	Java	89.6	8,602
MATE	2015	Java	92.5	550
Turbo	2015	C++	92.4	349

Figure 3.1: Benchmarks of different syntactic parsers
Image extracted from `https://spacy.io/usage/facts-figures#benchmarks`

An evaluation published by *Yahoo! Labs* and Emory University, as a part of a survey of current parsing technologies (Choi et al., 2015), observed that "spaCy is the fastest greedy parser" and its accuracy is within 1% of the best available (as we can see in Figure 3.1). The few systems that are more accurate are 20 times slower or more. Speed is an important factor when we want to implement complex systems that are faced with long texts or a large number of documents (as is our case, where we want to analyse all possible e-mails).

	ABSOLUTE (MS PER DOC)			RELATIVE (TO SPACY)		
SYSTEM	TOKENIZE	TAG	PARSE	TOKENIZE	TAG	PARSE
spaCy	0.2ms	1ms	19ms	1x	1x	1x
CoreNLP	0.18ms	10ms	49ms	0.9x	10x	2.6x
ZPar	1ms	8ms	850ms	5x	8x	44.7x
NLTK	4ms	443ms	*n/a*	20x	443x	*n/a*

Figure 3.2: Per-document processing time of various NLP libraries
Image extracted from `https://spacy.io/usage/facts-figures#benchmarks`

Choi et al. (2015) results and subsequent discussions helped spaCy develop a novel psychologically-motivated technique to improve spaCy's accuracy, which they published in joint work with Macquarie University (Honnibal and Johnson, 2015). For this reason we have chosen spaCy v2.2.1 which takes advantage of this technique.

Furthermore, not only in general but in each particular task (tokenisation, tagging and parsing), spaCy is the fastest if we compare it with other natural language processing libraries. This is shown in Figure 3.2, where we can observe both absolute timings (in ms) and relative performance (normalized to spaCy). The systems which have lower values are faster in their tasks.

Finally, spaCy has three pretrained model pipelines for Spanish with a very high accuracy (see Figure 3.3). These will help us to tokenise, tag and parse our messages in order to calculate the different style markers defined.

MODEL	SPACY	TYPE	UAS	NER F	POS	WPS	SIZE
es_core_news_sm 2.0.0	2.x	neural	89.8	88.7	**96.9**	*n/a*	**35MB**
es_core_news_md 2.0.0	2.x	neural	**90.2**	89.0	97.8	*n/a*	93MB
es_core_web_md 1.1.0	1.x	linear	87.5	**94.2**	96.7	*n/a*	377MB

Figure 3.3: Benchmark accuracies for the Spanish pretrained model pipelines
Image extracted from `https://spacy.io/usage/facts-figures#benchmarks`

3.2.2. spaCy's utilities

We can define spaCy as a Python natural language processing library specifically designed to be a useful library for implementing production-ready systems. For this reason, it has a lot of different utilities. However we are only going to need the ones carried out by the *Tokenizer* and the *Sentencizer*.

The spaCy's *Tokenizer* class is in charge dividing the given message into the different words that constitute it and obtaining several features about them. We are interested in the attributes that we can observe in Table 3.1. In addition to its part of speech, it gives us more information (that we are not interested in it) depending on its lexical category, such as its gender, number, verb tense or, even, the type of adverb.

Attribute	**Type**	**Explanation**
is_punct	bool	It indicates whether the token is a punctuation mark.
is_right_punct	bool	It indicates whether the token is a right punctuation mark (such as a right quote mark).
is_left_punct	bool	It indicates whether the token is a left punctuation mark.
is_bracket	bool	It indicates whether the token is a bracket.
like_url	bool	It indicates whether the token is an url.
like_email	bool	It indicates whether the token is an e-mail address.
lema_	string	Base form of the token, with no inflectional suffixes.
is_stop	bool	It indicates whether the token is a stop word.
pos_	string	Part of speech of the token.
is_oov	bool	It indicates whether the token is recognised by our spaCy's model and it has information about it
text	string	Verbatim text content.
idx	integer	The character offset of the token within the parent document.

Table 3.1: *Tokenizer*'s interesting attributes

The spaCy's *Sentencizer* class is in charge of establishing the boundaries between each sentence of the text. In this way, we are able to calculate metrics such as the average length of the sentences of the document.

3.3. Flask

Some modules implemented in this work have been developed as a web service. For this reason, it is necessary to use a framework that helps in the task of programming to easily and efficiently create this type of service. As we have also decided to work in the Python programming language, it is convenient that the framework we choose is developed in that language or is compatible with it. With these restrictions in mind, we chose the Flask[5] tool, which allows us to develop free open source web applications written in Python.

Flask is a minimalist framework written in Python that allows us to create web applications quickly and with a minimum number of lines of code. It is designed to make getting started quick and easy, with the ability to scale up to complex applications. Flask is simple and easy to apply in our development, it allows a cleaner backend when handling users, decreasing memory and speed to avoid server failures. It stands out for installing extensions or complements according to the type of project to be developed, that is to say, it is perfect for the rapid prototyping of projects. It includes a web server so we avoid installing one like Apache or Nginx. Its speed is better compared to other similar tools like Django. Generally, Flask's performance is superior due to its minimalist design in its structure. For these reasons we have chosen Flask in order to develop the required web services.

3.4. MongoDB

As we will see, we will need to store different types of data during the analysis of the e-mails. For this task we have chosen MongoDB[6] which is an open source, document-oriented, NoSQL database system.

Instead of storing data in tables, as is done in relational databases, MongoDB stores BSON data structures (a specification similar to JSON) with a dynamic schema, making data integration in certain applications easier and faster (Győrödi et al., 2015). This feature is perfectly adapted to our needs since, as we will see, the data structures we will handle will be variable. In addition, no powerful resources required to work with it and, thanks to the flexibility offered by being a NoSQL database, we can easily carry out modifications in our conceptual model of the database without having to worry about problematic changes between primary and foreign keys between tables. Moreover, it has official drivers for the Python programming language we will be working on.

[5] `https://flask.palletsprojects.com/en/1.1.x/`
[6] `https://www.mongodb.com/`

Chapter 4

Style Analyser

"- Marty McFly: Wait a minute, Doc. Ah... Are you telling me you built a time machine... out of a DeLorean?
- Dr. Emmett Brown: The way I see it, if you're gonna build a time machine into a car, why not do it with some style?"
— Back to the Future (1985)

In order to generate messages with the user's writing style, it is necessary to define parameters which will determine and describe it. For this purpose, we have developed a style analyser that extracts the messages written by the user and obtains the value of various metrics from them. Then it will be useful for analysing different user's e-mails and drawing conclusions about what parameters describe the writing style of each person more accurately.

In this section we are going to explain the architecture of this analyser (see Section 4.1) and each of the modules that compose it (they are explained in Sections 4.2, 4.3, 4.4, 4.5 and 4.6). Finally, we are going to present the behaviour of the execution with the Gmail account that is going to be analysed (this discussion can be looked up in Section 4.7).

4.1. Architecture

The first step when we are designing a system's architecture is to know its input and output. In this case, we want to implement a natural language processing system that analyses the writing style of e-mails. As we have previously mentioned, the stylometric analysis will be represented through chosen style markers. Therefore, our system's output is going to be that chosen metrics (they are explained in section 4.5) of each message.

In respect of the system's input, because of the nature of the problem we face, it is reasonable to think that it must be an e-mail. However, we do not have the corpus of e-mails to analyse. For this reason, our first step will be to extract the e-mails that will be analysed. Hence, our system's input is going to be the information of the Gmail user for accessing to the data that we are interested in. Therefore, we are going to develop a system which receives some information of a Gmail user as input and obtains different metrics for each message sent by the given user as output.

Once we clearly know the input and output of our system, we need to define the different steps that a message have to take for being analysed. In this manner, we are going to design a pipeline architecture with four different phases (extraction, preprocessing, typographic correction and measuring) as Figure 4.1 shows. Thus, we divide the original job in four

different and more simple tasks with distinct inputs and outputs required. This division into phases addresses both the need to atomise each of the steps to obtain the desired output, and to take advantage of benefits that a single indivisible system does not provide. One of these advantages is the possibility of working in parallel with each of the different phases. Another advantage, without a doubt, is the greater facility for the correction of errors in the pipeline. Thus, if an error of any kind is found in any phase, this will not affect the implementation of subsequent phases and it will not be necessary to modify the entire system. This, together with the fact that each phase stores its corresponding output using different MongoDB documents (see Section 3.4), allows us to change the behaviour of a phase (either in case of improvement or error correction of the implementation) avoiding to execute again the previous phases to the modified one, it would only be necessary to execute the changed phase and the ones that follow. Finally, it is also important to note the advantage of reusing each of the phases separately without having to rely on the others.

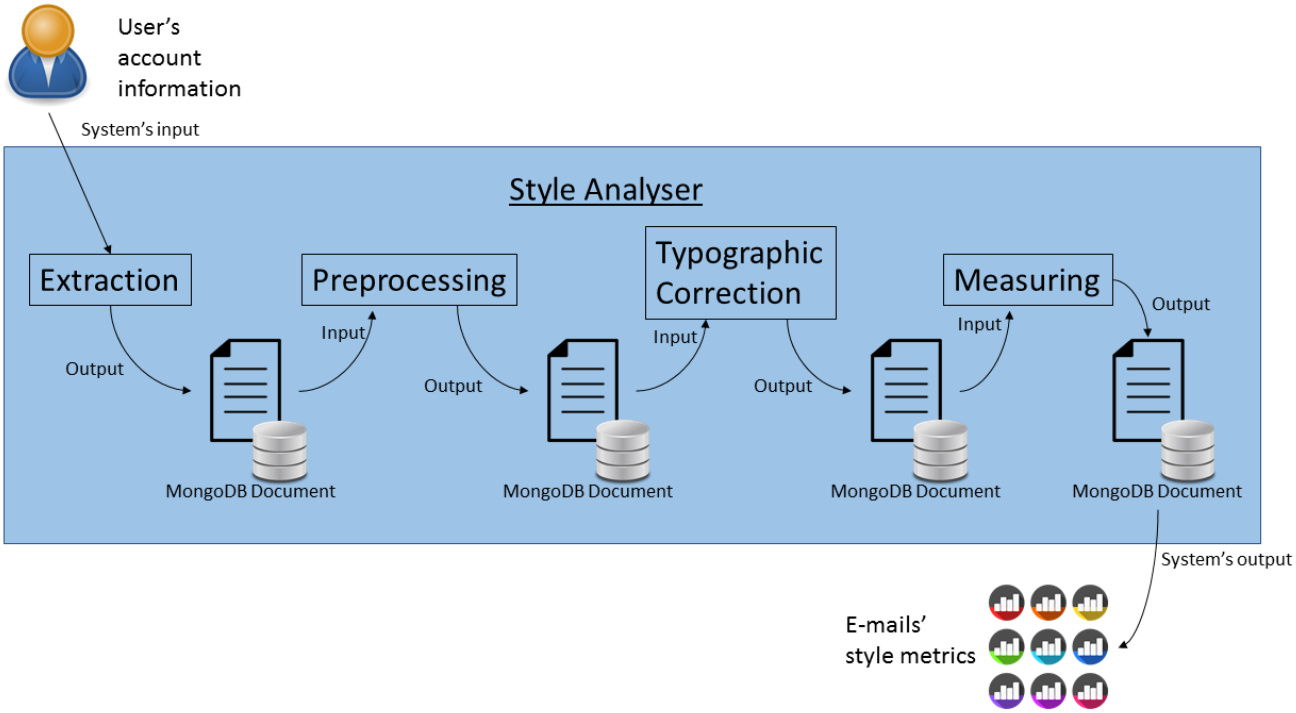


Figure 4.1: Pipeline architecture of the style analyser

As it is easy to deduce, each of these phases is going to be developed as a different module. This implementation will have the advantage that each module is going to be able to work independently from the other modules, which will allow them to work in parallel. That is to say, while a message is being extracted, other e-mails could be being preprocessed, corrected or measured if they have gone through the previous phases. This optimizes the time it takes for a message to be extracted until the respective metrics are calculated (it does not have to wait for the others to move to the next phase of the pipeline). In addition, the last three (preprocessing, typographic correction and measuring) have been implemented as web services using Flask (see Section 3.3), which facilitates their reuse even separately in other works and projects. Let us now briefly explain what each of the defined phases consists of.

The first step, extraction phase, consists of the extraction of each one of the sent

messages of the given user. In this task, we are going to take advantage of all the studied concepts about the Gmail API (see Section 2.1.5) and make use of every resource it provides us. Besides, we will try to minimize the consumed quota units in each extraction, which means we will only make the requests to the Google Servers that are strictly necessary. This first step is not just the task of extracting the resource that represents each sent message from the user's account, but also the job of transforming it to the format that the preprocessing module needs. Hence, the input of this module will be the same input as that of the complete system (information about Gmail user) and its output will be an extracted message ready for being preprocessed.

As for the second step, the preprocessing phase, consists of modifying the extracted message so that it can be interpreted by the spaCy's natural language processing model to be used. Some of the changes that a message could suffer in this phase are: the removal of the signature, the disposal of the replied messages which appears under the text, the elimination of soft break lines that quoted-printable codification (see Section 2.1.1.4) introduce in some messages, etc. This module also addresses the need to remove characters and structures that do not correspond to those used in a plain text such as bold or italic type styles, font sizes and fonts, enumerations or bulleted lists, etc. Likewise, its output is a message with its body as a plain text.

In the implemented metrics (as we will see in section 4.5) we will not take into account typographical errors (such as a spelling mistake). So we will need to fix them as much as possible, and this is the typographic correction module's task. In the same way, it is possible that some tokens do not belong to our spaCy model's vocabulary. Therefore, it will be necessary to know lexical-syntactic information about the token, such as its part of speech and its lemma. These are the task of the typographic correction module.

Finally, the measuring module is in charge of calculating all the style features chosen for this work. For that purpose, it receives a message (extracted by the extracting module) with a plain text format (thanks to the preprocessing module) free from typographic error (thanks to the typographic correction module) and obtains the result of measuring all the style markers selected in the given message.

As we have explained, the input of the extracting module is information about a Gmail user and the input of the rest of the modules is a single message. However, each module is independent from each other, which means that it is necessary to have a way of assembling all this modules. For this purpose, the *Analyser* class is developed (see Section 4.6). This entity is in charge of sending to each module the required input in order to obtain its output. Moreover, it presents the system to the user, communicates the information and captures the user's information (it performs a previous filtering to check that there are no formatting errors), such as the typographic correction of the errors found. In this manner, the architecture of our style analyser system is as shown in Figure 4.2 (in the following sections we will delve into each module of this system), which represents the UML (Unified Modelling Language) class diagram of it. In this figure we have avoided including both attributes and methods of each class, since with it we want to show the general structure of the system. In the sections corresponding to each of the packages and the *Analyser* class, their attributes and methods will be specified and explained.

As we wanted, the *Analyser* manages the communication between each UML package (which represent each of the mentioned modules). Thus, this UML class will transport the output of each module to the input of the subsequent phase so as to fulfil the pipeline established in Figure 4.1.

If we look at the relationship shared by the *Analyser* class and the *Extraction* package (specifically with the *Extractor* class of this module), we will notice that it is an uni-

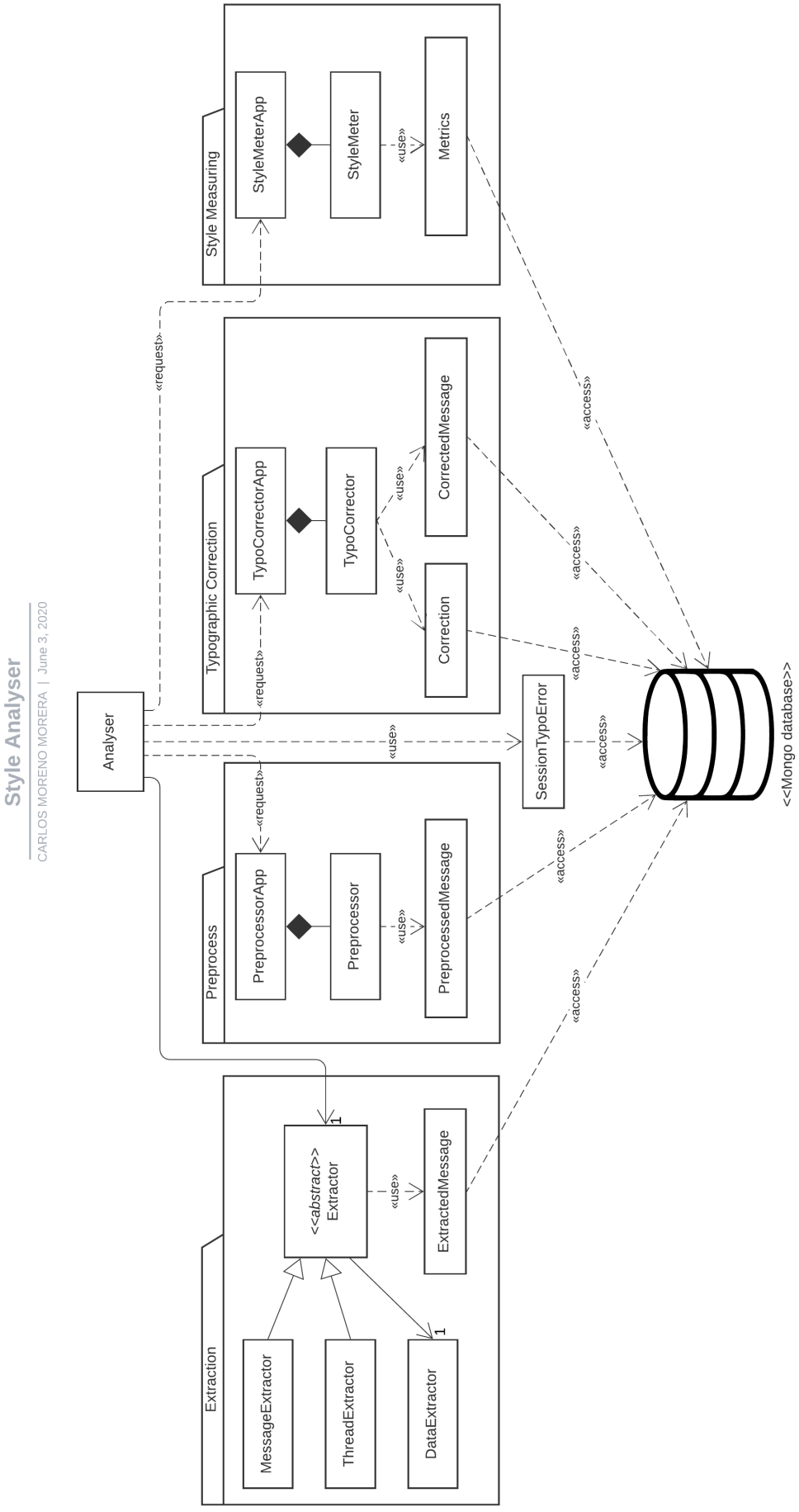


Figure 4.2: UML class diagram of the style analyser

directional binary association, what it means that the objects of the second are connected with the objects of the first. Furthermore, we can observe a multiplicity index in the arrowhead (the *Extraction*'s end), which means that the *Analyser* will be related with an only *Extractor* object (it will not be necessary to have more than one *Extraction* package in order to obtain all user's sent messages).

The rest of packages are "used" by the *Analyser*, through a POST HTTP request, because all of them are implemented as web services. It contacts with the module's app which is related with the module's main class (which is in charge of carrying out its corresponding task).

An important observation to mention is the fact that all packages interact with their corresponding classes, which act as DAO (Data Access Object), with the database used (with MongoDB technology as it is explained in Section 3.4). Their interaction is based on storing their results in it. The main advantage of this implementation is that it is not required to have enough dynamic memory in order to process every message at the same time. In addition to it, as we have explained, if an error is detected in an specific phase, it is not necessary to execute the previous modules again. With this in mind, it is reasonable to think that each module's main class, of the last three phases, will make use of the corresponding class with the purpose of saving its result, obviously after finishing its execution with the given message.

Below we only have to enter in detail of each of the packages and of the *Analyser*, in order to completely understand the style analyser.

4.2. Extraction module

The extraction module encapsulates all the necessary functionality in order to extract the given user's sent messages. As it is shown in Figure 4.3, this UML package has five different UML classes: *Extractor*, *MessageExtractor*, *ThreadExtractor*, *DataExtractor* and *ExtractedMessage*.

The main class of the above five is the *Extractor* class, which is an abstract class implemented by *MessageExtractor* and *ThreadExtractor* classes. The reason for implementing it as an abstract class with the abstract methods *get_list*, *get_resource* and *extract_sent_msg*, lies in the desire to minimise the number of quota units used during this process. Let's explain this in detail.

As we have see in the Table 2.1, to carry out the messages resource's operation costs five quota units and to perform the same operations for the thread's resource costs ten quota units. However, when the operation *messages.get* is invoked we get a single message, whereas when the operation *threads.get* is called we get as many messages as there are in the thread. Therefore, minimising the amount of quota units used depends on the number of messages and threads we have.

When we are in the extraction process, at first it is necessary to invoke a *list* method. It will return a list of, at least, 100 identifiers of the resource (message or thread). Then, these identifiers will be used to obtain (by calling the corresponding *get* method) each of the listed resources. If we want to obtain the identifiers of the remaining resources, we will have to invoke *list* again with the *nextTokenPage* obtained in the previous call. With this in mind, we are going to invoke the corresponding *list* method as many times as the result of applying the ceiling function to the division of the number of resources by 100; and we are going to invoke the corresponding *get* method as many times as the amount of resources the user has (this number is possible to know by calling the *get* method of the

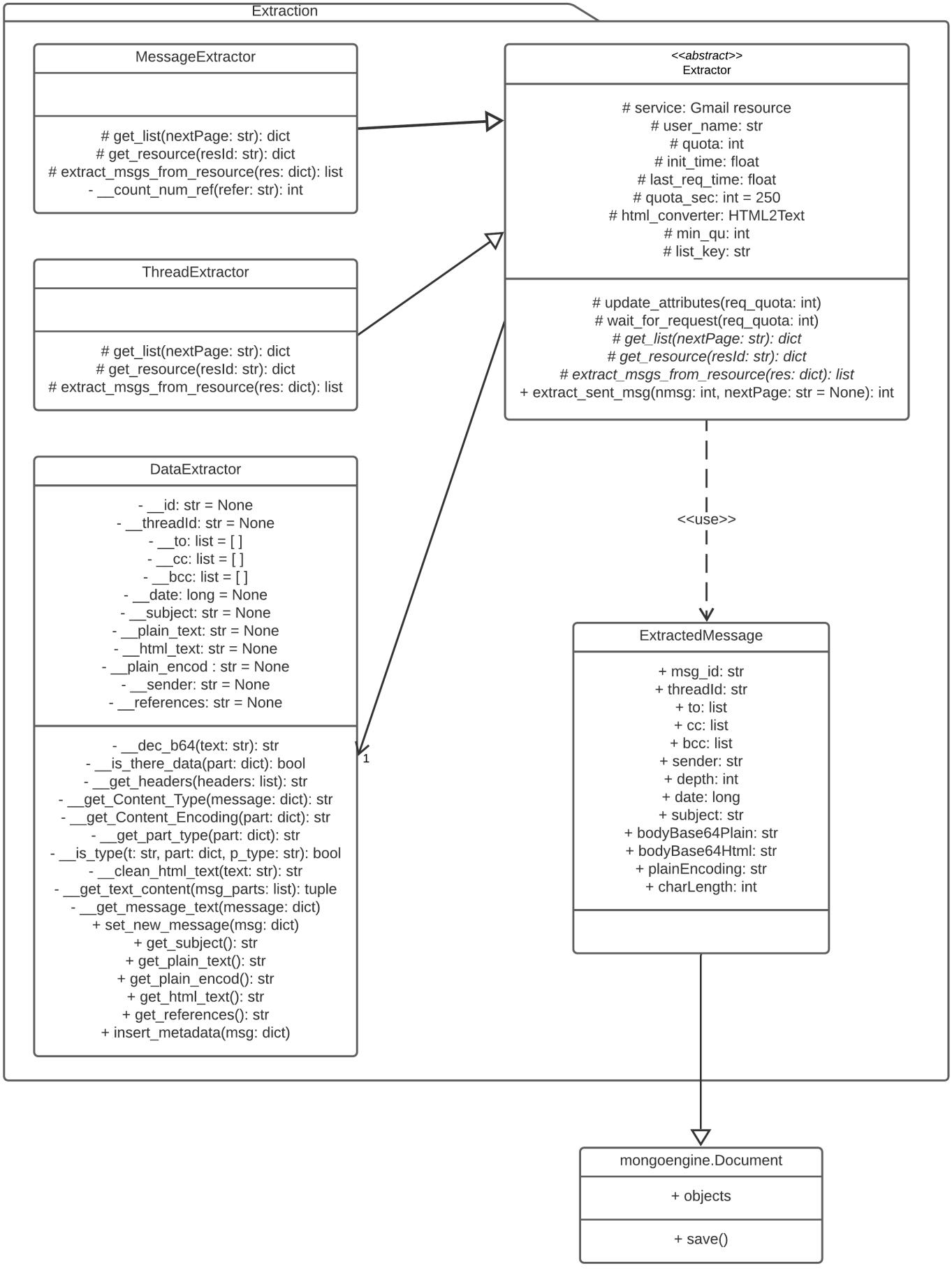


Figure 4.3: UML class diagram of the extraction module

labels resource and giving it the string value *SENT* as its parameter called *id*, which only consumes one quota units each time). Hence, the number of quota units inverted in an extraction process will be determined by the following formula:

$$Q = L \cdot \left\lceil \frac{N}{100} \right\rceil + G \cdot N$$

Where L is the cost in quota units of invoking the corresponding *list* method once, N is the number of resources that the user has and G is the cost in quota units of calling the corresponding *get* method once. It is important to remember that the division is the integer and not the real one.

Following the previous expression and the quota units cost of Table 2.1, we are able to claim that the number of quota units inverted in a message extraction process will be:

$$Q_M = 5 \cdot \left\lceil \frac{N_M}{100} \right\rceil + 5 \cdot N_M$$

Where N_M is the amount of sent messages that the user has. However, the cost in quota units of a thread extraction process will be determined by:

$$Q_T = 10 \cdot \left\lceil \frac{N_T}{100} \right\rceil + 10 \cdot N_T$$

Where N_T is the number of sent threads that the user has. Consequently, when we obtain that $Q_M < Q_T$, we will save more quota units by executing a message extraction process and, when $Q_T < Q_M$, it will happen by executing a thread extraction process.

Returning to the extraction module, even though the choice between the two types of extraction is done by the Analyser (see Section 4.6), it is necessary to implement both possibilities. For this reason, *Extractor* class was implemented as an abstract class with the methods related to the *list* and *get* functions of the Gmail API: *get_list* (which calls the corresponding *list* method) and *get_resource* (which invokes the corresponding *get* method). In addition to them, we can find the *extract_msgs_from_resource* as an abstract method. This function is in charge of extracting the necessary information from the corresponding resource in order to obtain a list of messages (in the case of the message resource the list has only one item) which are going to be stored in the database. In other words, it transforms a message (or a thread of messages) with the structure explained in Section 2.1.5.4 into the following structure (in the case of the thread resource each message will be transformed to the following structure):

```
{
    'id' : string,
    'threadId' : string,
    'to' : [ string ],
    'cc' : [ string ],
    'bcc' : [ string ],
    'sender' : string,
    'depth' : int,                  # How many messages precede it
    'date' : long,                  # Epoch ms
    'subject' : string,
    # Body as plain text encoded using base64
    'bodyBase64Plain' : string,
    # Body as html text encoded using base64
    'bodyBase64Html' : string,
    # Original encoding of the body as a plain text
```

```
    'plainEncoding' : string,
    'charLength' : int
}
```

Once the message has this structure, it is ready to be saved in the database, because of, as we can observe in Figure 4.3, the dictionary keys are the same as the attributes of the *ExtractedMessage* class (which inherits from the *mongoengine.Document* class, allowing it to insert elements in the database). Indeed, the *extract_msgs_from_resource* method returns a list of *ExtractedMessage* objects.

In addition to the explained abstract methods, in the *Extractor* class we can find the *extract_sent_msg*, which is in charge of the extraction algorithm that we mentioned before (invoke the corresponding *list* method, for each identifier get the resource, call the function *extract_msgs_from_resource*, etc.). During this process, the *Extractor* must check that it does not exceed the set limit of quota units, both the daily limit and the secondly limit. Once the daily limit is reached, the process must stop. In the case of the secondly limit, the *Extractor* must stop and wait until it can continue using the Gmail API operations. This is the task of *update_attributes* (which updates the time and quota attributes such as *quota*, *quota_sec*, *last_req_time* and *init_time*) and *wait_for_request* methods.

In respect of the *Extractor* class, there is an only remaining detail that should be mentioned. It has an attribute called *html_converter*. This attribute is an object of the *HTML2Text* class from *html2text* Python's library[1]. As we need the e-mail in plain text, in case the extracted message does not have it in this format, we can use this attribute to transform the HTML text into plain text.

If we observe the *Extraction* package, we will also find the *DataExtractor* class, which is related with the *Extractor* class by an uni-directional binary association with a multiplicity index in the arrowhead (the *DataExtractor*'s end). It performs the task of extracting the information of a given e-mail. To this end, it goes through the headers list (where information as the recipient can be found) and the MIME message parts tree studied in Section 2.1.1.2, in order to get the message body. Likewise, once an e-mail is extracted from Gmail API, the *DataExtractor* class receives it and acquires all the required information from it.

4.3. Preprocessing module

The preprocessing module receives the message with the structure given by the extraction module and modifies the e-mail so that it can be interpreted by the spaCy's pretrained model. As it is shown in Figure 4.4, this UML package has three different UML classes: *PreprocessorApp*, *Preprocessor* and *PreprocessedMessage*.

First of all, we can observe the *PreprocessorApp* class. It inherits from *Flask* class (see Section 3.3), which implements a simple web service. Consequently, if we want to preprocess a message, it will be necessary to execute a POST HTTP request with the e-mail as a *json* in it. Having done so, the *preprocess_message* method will be invoked and send the given message structure to the *Preprocessor* class by calling its only public method: *preprocess_message*. There is also the possibility of transmitting the user's e-mail signature to the *Preprocessor* (so that it can be removed from the different messages) by including it as an string in the sent *json*.

The main class of this UML package is the *Preprocessor* class. It is in charge of modifying the given message. For this reason, it has different methods which implements

[1] `https://pypi.org/project/html2text/`

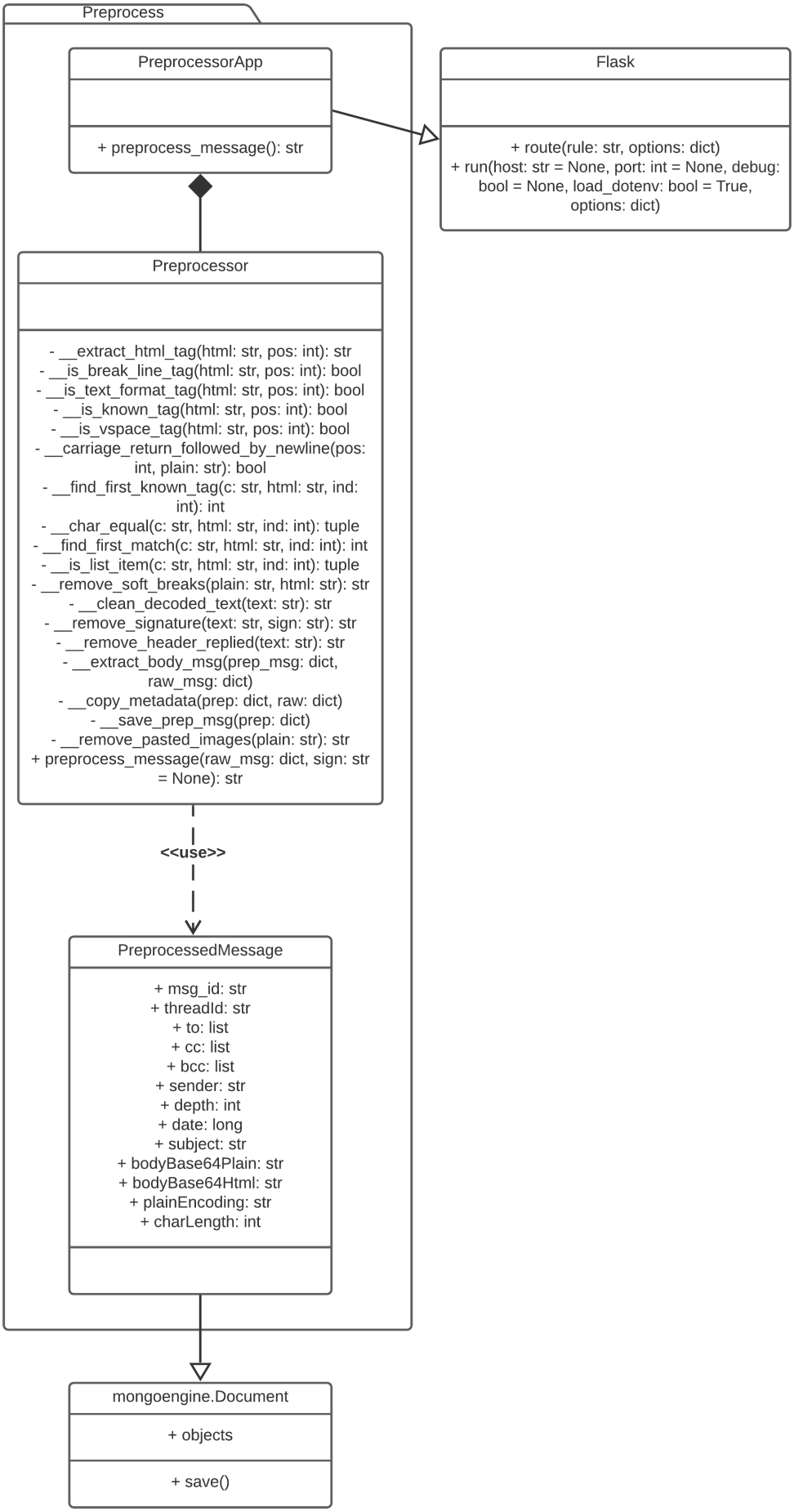


Figure 4.4: UML class diagram of the preprocessing module

the distinct tasks that it has to carry out.

The first task this module performs is to filter those e-mails whose message body as plain text is empty, which means that they lack the *bodyBase64Plain* field. As our purpose is analyse the writing style of the user, we are not interested in e-mails without text. Thus, these messages are discarded.

Then, the images inserted in the message body (not as an attachment) are removed by calling the *__removed_pasted_images* method. This function make use of the simple Python's regular expression r'\[image:[^\]]+\]', detects the position of the different images with it and takes them away.

Once pasted images are removed, the *__extract_body_msg* method removes the text of replied e-mail (if it exists) and the soft break lines inserted in the body, as a consequence of the established format in Gellens (1999). When someone replies an e-mail from a Gmail account, the replied message is automatically included under the response (indeed it is possible to intersperse the answer and the responded text). As it is not a written composed by our user, this copied text must be taken away. To this end, the *Preprocessor* class creates an object of the *EmailReplyParser* class of the *email_reply_parser*[2] Python's library. With its *parse_reply* method, only the response is obtained with the replied message's header automatically included (*EmailReplyParser* class does not remove it). However, such header is easy to detect by using regular expressions, due to it has an specific format as the following line (written in Spanish):

El mié., 27 may. 2020 a las 11:11, Name (<example@mailserver.com>) escribió:

The designed regular expression detects this type of sentences with the moment (date and time) and the sender. Once *Preprocessor* knows its position, it is possible to take it away.

A similar problem appears with forwarded messages. Nevertheless, unlike replied e-mails, it is not possible to detect if the user has interspersed new text in the forwarded written. For this reason, *Preprocessor* detects the forwarded header, which indicates the beginning of the resent message, and deletes all the text from it.

In addition to the replied or forwarded text, we find the problem of the inserted soft break lines in order to follow the standard format for sending e-mails. We have implemented two solutions for this issue in *__clean_decoded_text* and *__remove_soft_breaks* methods. The first function deletes all soft break lines in messages encoded with quoted-printable (see Section 2.1.1.4). The second, compares the message body as HTML text and as plain text and removes all soft break lines that do not appear as an HTML tag. Moreover, during this process we detects characters that should not appear in the plain text. For instance, Gmail delimits the text in bold with the symbol "*" (there are more examples as the beginning of a bulleted list, an enumeration or the change of font or font size). As in the HTML text it will appear between two tags, we recognise this fact and take the delimiter character away. In this way we are able to obtain a real plain text.

The last modification made by the preprocessor is the removal of the signature. This only happens if the user has provided it to the system, since the recognition of the signature is a complex problem that is not the objective of this work. The *__remove_signature* method is is responsible for carrying out that task.

Once an extracted e-mail is preprocessed, it is ready to be saved in the database. As it happened with the *ExtractedMessage* class, the *PreprocessedMessage* class inherits from the *mongoengine.Document* class, allowing it to insert elements in the database. If we compare the *ExtractedMessage* and *PreprocessedMessage* class, we will realise that they have the

[2] `https://pypi.org/project/email_reply_parser/0.1.0/`

same attributes, so a preprocessed message has the same structure as an extracted one.

4.4. Typographic correction module

The typographic correction module receives the message with the structure given by the preprocessing module and detects the typographic errors present in the given e-mail. As it is shown in Figure 4.5, this UML package has four different UML classes: *TypoCorrectorApp*, *TypoCorrector*, *CorrectedMessage* and *Correction*.

As it happened with *PreprocessorApp*, *TypoCorrector* inherits from *Flask* class and, thanks to it, this class implements a simple web service. However, unlike *PreprocessorApp*, *TypoCorrector* has two different methods which carry out different tasks. These two functions correspond to the two *TypoCorrector*'s public method with the same name. Thus, if we want to invoke one of these public methods, it will be necessary to execute a POST HTTP request with an e-mail, in order to be corrected (in the case of the method *correct_msg*), or with the unrecognised token (which has been wrongly classified as "out of vocabulary" by our spaCy's model) that is going to be saved (we will explained both tasks in detail later). Each one of them is going to have a different url address.

The main class of this UML package, as it happens with the rest of packages, is the *TypoCorrector* class. It is in charge of detecting the typographic errors and correcting them if it is possible. For this purpose it makes use (as an attribute) of an spaCy's pretrained model, specifically the one called *es_core_news_md*[3].

The first public method that we are going to explain is *correct_msg*, which receives as parameters a message and an index. The method's parameters are originally a preprocessed message with its structure and the index as 0, which indicates that the e-mail must be corrected from the beginning, because it points the word from which the typographic correction should be made. When the function finishes its operations, it returns a dictionary with the following structure:

```
{
    'typoCode': <enum 'TypoCode'>,
    'index': int,
    'typoError': str,
    'token_idx': int,
    'message': {
        'id' : string,
        'threadId' : string,
        'to' : [ string ],
        'cc' : [ string ],
        'bcc' : [ string ],
        'sender' : string,
        'depth' : int,                  # How many messages precede it
        'date' : long,                  # Epoch ms
        'subject' : string,
        'bodyPlain' : string,
        'bodyBase64Plain' : string,
        'plainEncoding' : string,
        'charLength' : int,
        'corrections' : [
        {
            'text': str,
            'is_punct': bool,
```

[3] https://spacy.io/models/es

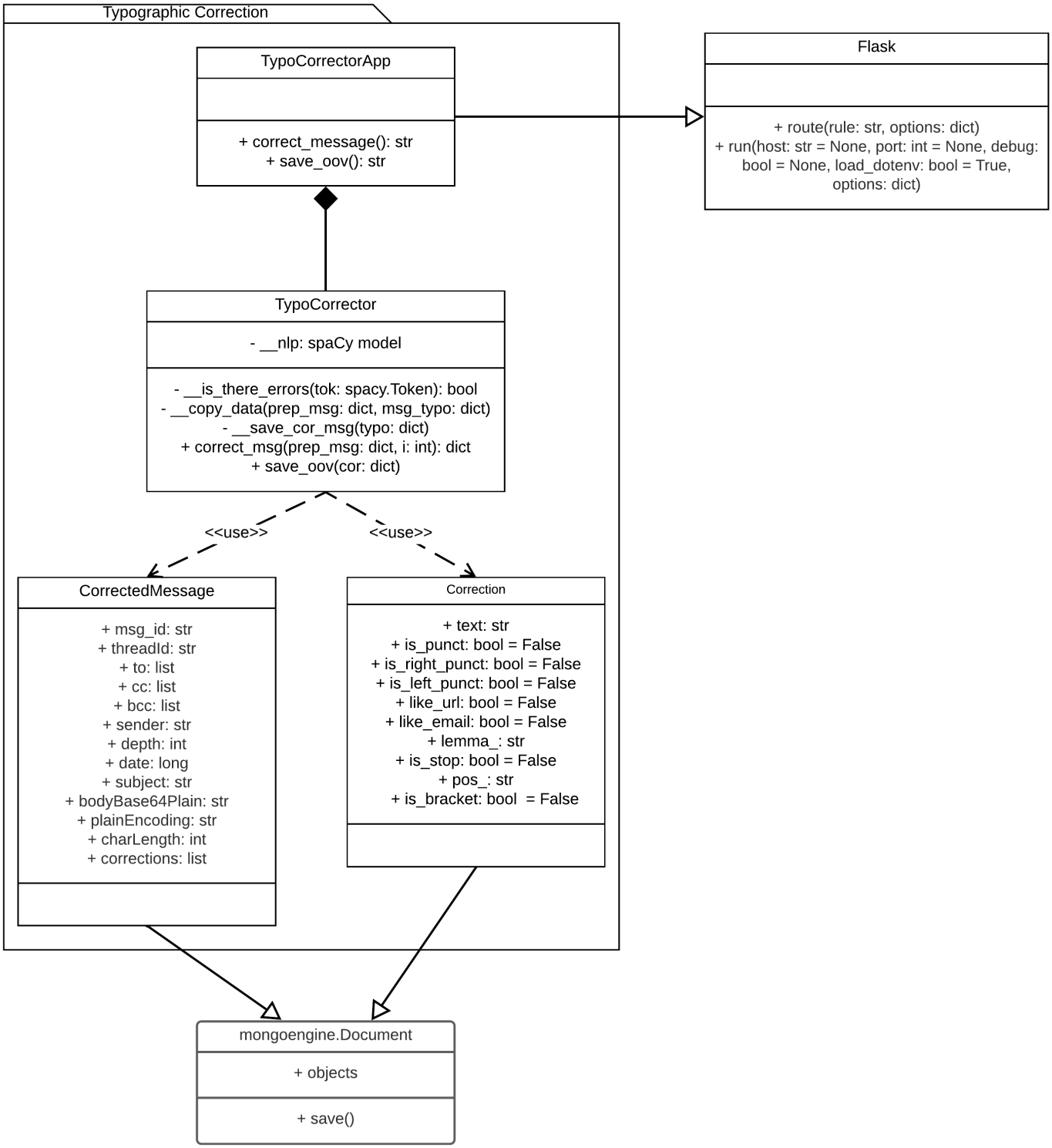


Figure 4.5: UML class diagram of the typographic correction module

```
            'is_right_punct': bool,
            'is_left_punct': bool,
            'like_url': bool,
            'like_email': bool,
            'lemma_': str,
            'is_stop': bool,
            'pos_': str,
            'is_bracket': bool,
            'position': int
        }
        ]
    }
}
```

If no typographic errors are detected in the text or the user's help is not needed, the *message* field is previously saved in the database, by using the *CorrectedMessage* class (its attributes perfectly match with the fields of the *message* field dictionary), the *typoCode* field will take the value *successful* and the *typoError* and *token_idx* fields will take the value *None*. However, in other case, the execution of the system changes.

The first task the *correct_msg* method performs is to filter those e-mails whose message body as plain text is empty, due to the preprocess could produce this result, such as in forwarded messages without new text. In this case, the *typoCode* will take the value *notAnalysed*.

Then, it checks from the given index onwards if one token is recognised by our spaCy's model as "out of vocabulary". If this happens, the word is searched in the database of corrections (which is easy to manage thanks to the *Correction* class) in case it was previously stored in it as a non-out-of-vocabulary token (in this database we have all words that are not really a typographic error, but they are not recognised by our natural language processing model). If the word appears in it, the information of this "correction" is appended to the *"corrections"* list (each of its elements has the same field as the *Correction* class' attributes) and the execution continues as usual, as if no error has been detected.

On the other hand, if the detected "out of vocabulary" token is not in our *Correction* database, which means that it could be a real typographic error or a existent word which is not recognised by our spaCy's model and not previously stored, the *Analyser* class (out of this module), with the help of the user, will be in charge of determining if it is a real typographic error and correcting it in that case. For this reason, the *TypoCorrect* will return the mentioned structured with the *typoCode* field taking the value *typoFound*, the *word* one with the text of the detected token and the *token_idx* with the character position of the beginning of the found word. The *index* field will always take the value of the position of the last analysed word, if there are no errors detected it will be the number of words in the message.

Once the *Analyser* has determined if the given word is a real typographic error, and corrected it in that case, it will invoke again the *correct_msg* method, through a POST HTTP request, and it will send as a parameter the returned *message* field (probably with the message body changed or with a new element in *corrections* list) and with the corresponding index. For example, if the detected token was not a real typographic error, the index will be the position after the word (due to the previous words has been analysed yet). This is the advantage of this function, it allows us to start a new typographic correction or continue a previously started one, because it admits as the *prep_msg* parameter a preprocessed message or a partially corrected message.

In this section, we have explained when the *Correction* queries are carried out, but

we have not said anything about when its elements are inserted. For this purpose, the *save_oov* method was implemented. If the *Analyser* determines that the returned word is not a typographic error, it can carry out a POST HTTP request in order to save the information of this word in the database for future cases.

4.5. Measuring module

The measuring module is in charge of calculating all the selected writing style metrics. In order to measure these features, it receives from the *Analyser* class a corrected message with the following structure (which matches with the stored messages' structure):

```
{
    'id' : string,
    'threadId' : string,
    'to' : [ string ],
    'cc' : [ string ],
    'bcc' : [ string ],
    'sender' : string,
    'depth' : int,                  # How many messages precede it
    'date' : long,                  # Epoch ms
    'subject' : string,
    'bodyBase64Plain' : string,
    'plainEncoding' : string,
    'charLength' : int,
    'corrections' : [
    {
        'text': str,
        'is_punct': bool,
        'is_right_punct': bool,
        'is_left_punct': bool,
        'like_url': bool,
        'like_email': bool,
        'lemma_': str,
        'is_stop': bool,
        'pos_': str,
        'is_bracket': bool,
        'position': int
    }
    ]
}
```

As we can see in Figure 4.6, the style measuring package has three different classes with a class diagram similar to that of the preprocess package. These three classes are: *StyleMeterApp*, *StyleMeter* and *Metrics*.

As with the two previous modules, this package implements a Flask web service which can be used through a POST HTTP request with the message as a *json* in it. Having done so, the *measure_style* method of the *StyleMeterApp* class will be invoked and send the given message structure to the *StyleMeter* class by calling its only public method: *measure_style*.

The main class of this UML package is the *StyleMeter* class. It is in charge of calculating the style features. For this reason, it has different methods which implement the distinct style markers that it has to evaluate.

As the reader is able to deduce after presenting the previous sections, the *Metrics* class

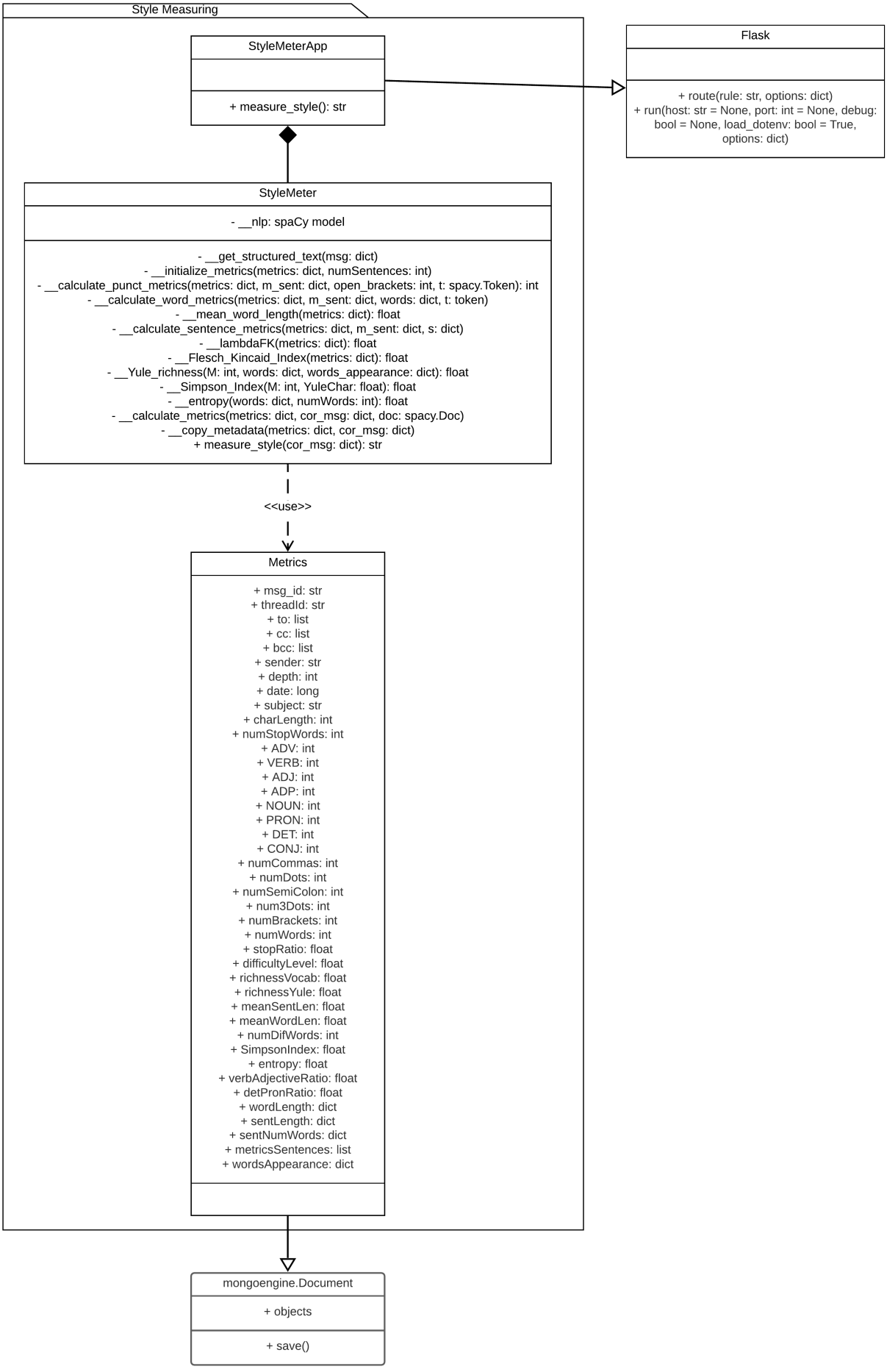


Figure 4.6: UML class diagram of the measuring module

will store in the database the results of measuring each message. The *StyleMeter* class will use it once it has calculated all the style characteristics.

We have used 31 lexical-syntactic features (due to previous studies, such as Homem and Carvalho (2011), yield encouraging results with lexical-syntactic features), following the classification of Abbasi and Chen (2008) (which categorised stylistic features as lexical, syntactic, structural, content-specific and idiosyncratic style markers), and we will now divide them into four categories in which we have grouped them according to their usefulness in terms of what type of conclusions we can infer from each of them. These categories are: part of speech features (see Section 4.5.1), punctuation features (see Section 4.5.2), vocabulary features (see Section 4.5.3) and structural features (see Section 4.5.4). We must not confuse this latter category (which belongs to the lexical features of the classification given in Abbasi and Chen (2008)) with the structural metrics explained in Abbasi and Chen (2008). Some of the popular metrics which are not used in this work, belong to the structural, content-specific and idiosyncratic style markers of Abbasi and Chen (2008), but there are others which belong to the same categories as the explained metrics (lexical and syntactic).

The choice of the metrics presented below, some essentially simple, has been directed by the objective of finding easily explainable characteristics that set the parameters of the style of writing according to the recipient of the e-mail, and then be able to use this study to develop, in future projects, systems of natural language generation of e-mails that take into account this factor. For this reason, some excessively complex metrics, although popular in stylometry, have been avoided and an attempt has been made to prioritize the explainability of the chosen features.

Finally, we are going to relate the explained style markers with their implementation (see Section 4.5.5) in the *Metrics* class.

4.5.1. Part of Speech metrics

We will call our part of speech metrics as the syntactic features which have to do with the part of speech of each word of the e-mails. Following the suggestion of Holmes (1985), we count the number of nouns, verbs, adjectives, adverbs, pronouns, determinants, conjunctions and prepositions of each text. By calculating this, significant stylistic traits may be found, because as Somers (1966) claims: "A more cultivated intellectual habit of thinking can increase the number of substantives used, while a more dynamic empathy and attitude can be habitually expressed by means of an increased number of verbs. It is also possible to detect a number of idiosyncrasies in the use of prepositions, subordinations, conjunctions and articles".

In addition to this metrics, we calculate the verb-adjective ratio and the determinant-pronouns ratio, extracted from Antosch (1969) and Brainerd (1974), respectively.

4.5.2. Punctuation metrics

In order to extract conclusions from this syntactic metrics, and following the example of Calix et al. (2008), we calculate the amount of commas, periods, semi-colons, ellipsis and pair of brackets. With these features we can reach conclusions such as the structural complexity of a message (since, for example, juxtaposition structures appear in the presence of some of these scores), the division into sentences of the message or the need for clarification of the text transmitted (for example, by analysing the amount of brackets).

4.5.3. Vocabulary metrics

In terms of the used vocabulary, we work with the "bag of words" metrics, in other words, we note how many times each different word is used in a message. Of course this is not the only metric that we can categorise as a vocabulary feature and from which we can extract conclusions about the vocabulary used. There are many others which try to set the parameters of, for instance, the difficult of the vocabulary or its richness. Furthermore, from the computing of the bag of words, we are able to easily obtain other style marker chosen which also belongs to this category of vocabulary features: the amount of different words in each text, proposed in Ril Gil et al. (2014) and in Corney et al. (2001).

As for the difficulty level, it determines the level of education that someone needs to have if they are to understand the text. There are several indices available to calculate this level, such as the proposed in Dale and Chall (1948), the Gunning Fog Index (Gunning, 1968) or the Flesch-Kincaid index (DuBay, 2004), although the latter is the most commonly documented and cited. The expression which determines the Flesch-Kincaid index is the following:

$$I_{FK} = 1.599\lambda - 1.015\beta - 31.517$$

Where λ is the mean of one-syllable words per 100 words, and β is the mean sentence length measured by the number of words. However, as our spaCy's pretrained Spanish model (see Section 3.2) is not able to divide words by syllables, we determine λ as the mean of words with two or less characters per 100 words.

In respect of the richness of the vocabulary, we have chosen two different metrics. The first that we are going to explain is the one proposed by Honoré (1979), which determines the richness of the vocabulary based on the total unrepeated words used in the text. The following formula defines it:

$$R_H = \frac{100 \log(M)}{M^2}$$

Where M is the number of different words in the text. However, as Ril Gil et al. (2014) claims, depending on the type of document being analysed, the calculation of R_H has more or less validity (for instance, certain specialist articles, as their nature, requires constant repetition of words). As a consequence of this, another definition of richness of vocabulary is proposed by Yule (2014). This richness marker, that we are going to use as our second richness of vocabulary style marker, is called Yule's characteristic and defined with the following expression:

$$K = \frac{10^4 \left(\sum_{i=1}^{\infty} i^2 V_i - M\right)}{M^2}$$

Where M is the number of different words in the text and V_i is the number of words that appear i times in the document.

From Yule's Characteristic we are able to calculate the Simpson's Index (denoted as D), defined in Simpson (1949). This famous metric is understood as the measurement of diversity based on the change that the two members of an arbitrary chosen pair of word tokens will belong to the same type. To calculate D it is necessary to divide the total number of identical pairs in the sample by the number of all possible pairs, that is to say, what the following expression defines:

$$D = \frac{\sum_{i=1}^{\infty} i(i-1)V_i}{M(M-1)}$$

Where we are maintaining the Yule's Characteristic notation. However, as we have transmitted in advance, it is possible to calculate the Simpson's Index if we know the value of Yule's Characteristic. This relationship is defined by the following expression (and we are going to use it in the implementation in order to speed the computing):

$$10^{-4}K = D\left(1 - \frac{1}{M}\right)$$

Vocabulary distribution can also be measured by using a concept linguists have borrowed from thermodynamics and applied to communication theory: entropy (used in Holmes (1985)). In literary text it is true that with an increase in internal structure, entropy decreases, and with an increase in disorder or randomness, the measure of entropy increases. The expression for the entropy of a system (vocabulary in this case) is:

$$H = -\sum_{i=1}^{\infty} p_i \log(p_i)$$

Where p_i is the probability of appearance of the i-th lemma (found by dividing the number of occurrences of that lemma by the total number of words in the text). Due to the value will change according to how much text is analysed, the formula may be refined in order that works of different length may be compared. In this way, as it is proposed in Holmes (1985), the following expression determines absolute diversity for any length text as 100, while absolute uniformity remains zero:

$$H = -100\sum_{i=1}^{\infty} p_i \frac{\log(p_i)}{\log(M)}$$

In addition to the words distribution features (which are the bag of words and the amount of different words), the level of difficulty, the richness of vocabulary (which is measured by the formula proposed in Honoré (1979) and the Yule's Characteristic), the diversity (represented by the Simpson's Index) and the internal structure of the vocabulary (which is measured by the entropy), we have defined other four style markers which also allow us to extract conclusions about some feature of the vocabulary of the message. The first of these is the most popular and old style marker: the mean word length. Researchers as Ril Gil et al. (2014) claim that it is "directly connected with the richness of the author's vocabulary and measures his or her ability to use complex words", due to it is considered that complex words are formed by three or more syllables that do not represent proper nouns, prefixes, suffixes or compound words. Thus, Ril Gil et al. (2014) propose an expression similar to the following one in order to calculate it:

$$L_W = \frac{\sum_{i=1}^{\infty} i * C_i}{N} \cdot 100$$

Where C_i is the number of words with i characters and N is the number of words used. This formula is analogous to the expression proposed by Ril Gil et al. (2014), except that with the one that we have presented the punctuation marks are removed from the numerator.

The second of these writing style metrics is the measurement of words length frequency distribution, that is to say, how many words with one character appear in the document, with two characters and so on up to the length of the longest word. Despite of being strongly influenced by the language, it is used in researches as Corney et al. (2001) and Kemp (1976), as it is claimed in Allen (1974): "Each writer, however, will have his own

curve, so that although English (and German) texts in general peak at three letters, the writings of John Stuart Mill peak at two and those of Shakespeare peak at four". Our interest will then focus on checking whether, in addition to depending on the author, this metric varies according to the recipient of the e-mail.

The rest of vocabulary features are related to the stop words present in the text. The simplest of those metrics is the style marker which consists of calculating the total number of stop words (denoted as T_S). On the other hand, as it is proposed in Ril Gil et al. (2014), we will calculate the stop words ratio, which is defined with the following expression:

$$S_W = \frac{T_S}{N} \cdot 100$$

4.5.4. Structural metrics

We will denote by structural metrics those features that we obtain directly from the construction of the analysed text. Some of these style markers are as simple as the total number of characters in the body of the e-mail or the absolute number of words in the e-mail, both used in researches such as in Corney et al. (2001) and Ril Gil et al. (2014).

Most of these features are sentence length dependent. Both Tallentire (1972) and Kjetsaa (1979) agree that summary measures such as average sentence-lengths are of little use in stylometry studies but distributions of sentence-lengths can be useful, even on their own. Taking into account the above, we will find both the distribution of the length of the sentences (calculated in number of characters and number of words) and the average length of the sentences in a message found by the number of words, as it is proposed in Corney et al. (2001). For the first one, we are going to store the number of sentence with length one, two, three and so on up to the length of the longest one, by measuring it using both the number of characters and the number of words.

4.5.5. Relationship between metrics and their implementation

Every explained style metrics are stored as an attribute of the *Metrics* class. The relationship between them and the presented style features and the categorisation of these style markers is exposed in Table 4.1.

There is only one attribute that we have not mentioned and does not appear in Table 4.1: *metricsSentences*. This attribute is a list of as many items as there are sentences in the document and each of them has the following dictionary structure:

```
{
    'numStopWords': int,
    'ADV': int,
    'VERB': int,
    'ADJ': int,
    'ADP': int,
    'NOUN': int,
    'PRON': int,
    'DET': int,
    'CONJ': int,
    'numCommas': int,
    'numDots': int,
    'numSemiColon': int,
    'num3Dots': int,
    'numBrackets': int,
```

Feature Category	Field name	Explanation
Part of speech	ADV	Number of adverbs
	VERB	Number of verbs
	ADJ	Number of adjectives
	ADP	Number of prepositions
	NOUN	Number of nouns
	PRON	Number of pronous
	DET	Number of determinants
	CONJ	Number of conjunctions
	verbAdjectiveRatio	Verb-adjective ratio
	detPronRatio	Determinant-pronouns ratio
Punctuation	numCommas	Number of commas
	numDots	Number of periods
	numSemiColon	Number of semi-colons
	num3Dots	Number of ellipsis
	numBrackets	Number of pair of brackets
Vocabulary	wordsAppearance	Bag of words
	numDifWords	Number of different words
	difficultyLevel	Modified Flesch-Kincaid index (I_{FK})
	richnessVocab	Honoré (1979) vocabulary richness (R_H)
	richnessYule	Yule's characteristic (K)
	SimpsonIndex	Simpson's index (D)
	entropy	Entropy (H)
	meanWordLen	Mean word length (L_W)
	wordLength	Word length distribution
	numStopWords	Number of stop words
	stopRatio	Percentage of stop words (S_W)
Structural	charLength	Number of characters
	numWords	Number of words
	sentLength	Sentence length distribution (number of characters)
	sentNumWords	Sentence length distribution (number of words)
	meanSentLen	Average word count per sentence

Table 4.1: Classification of the style metrics

```
    'wordLength':
    {
        '1': int,
        '2': int,
        ...
    }
    'charLength': int,
    'numWords': int,
    'stopRatio': float,
    'meanWordLen': float
}
```

With this dictionary, we calculate these metrics for each sentence, instead of evaluating them on the entire message.

4.6. Analyser class

The *Analyser* class in charge of managing all phases in the pipeline, in other words, it sends to each module the required input in order to obtain is output. Besides, as it has been explained in Section 4.4 where the typographic correction module was presented, it asks the user the necessary information for the purpose of detecting and correcting, if it is required, the found typographic errors. In addition to it, as we can see in Figure 4.7, this class is able to store information in the database and extract it through the *SessionTypoError* class.

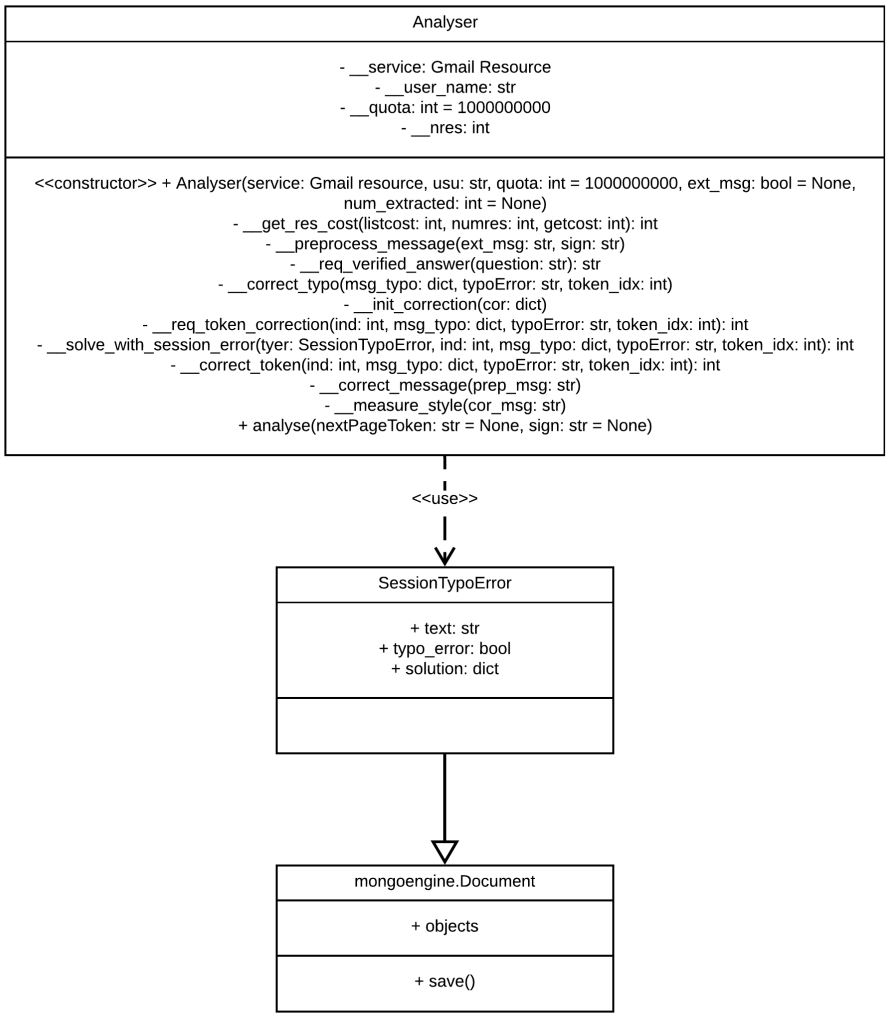


Figure 4.7: UML class diagram of the Analyser

The *Analyser*'s class constructor has an special interest in this system, due to it chooses the type of extraction that is going to be executed: a message extraction or a thread extraction. With the purpose of making this choice, the *get* method of the labels resource is invoked in order to obtain the value of the fields *messagesTotal* and *threadsTotal* of the *SENT* label structure (see Section 2.1.5.3). With this values tha *Analyser* is able to calculate the quota units cost (as we see in Section 4.2) of each type of extraction (this task is carried out by the *__get_res_cost* method) and choose the one which minimises

it. After deciding it, it gives effect to the choice by creating the corresponding object with the type of extraction (*MessageExtractor* or *ThreadExtractor*).

Once an *Analyser* object is created, the entire system can start its execution by calling the *analyse* function (the web services of the modules which represent the last three phases in the pipeline have to be running). During the execution of this method, the only module that will require the attention of the *Analyser* is the typographic correction module. The rest of the packages will only need this class to provide the input messages and collect their output structures.

If the *TypoCorrector* detects a typographic error, the first action that the *Analyser* carries out is searching in the database if that word was previously found and corrected it. For this purpose, the *SessionTypoError* stores the common typographic errors that a user made (this collection is dropped at the beginning of each execution) and how to solve it (the *solution* field has the same structure as the items of the list *corrections* of the structure given by the *TypoCorrector*). If it is a real typographic error, the *typo_error* field will take the value *True* and in the *solution* dictionary the text that should replace the word is stored. If it is not, the *solution* dictionary will be appended to the *corrections* list and the message will go on being corrected.

In the case that this typographic error is not stored, the *Analyser* will ask the user whether the message has to be discarded (this option allows the user to remove from the pipeline, for instance, e-mail written in other languages). If it is discarded, the *Analyser* sends then next message ready to be corrected to the typographic correction module. If it is not discarded, the *__req_token_correction* method is invoked. This function will ask the user whether the word is a real typographic error. If it is, there are two solutions: remove the token from the text or rewrite it. Either way, at the end the user is going to answer the question: "Do you want to save this information for this session?" In this way the user will decide whether the solution is inserted in the collection managed by *SessionTypoError* in case the same error is detected again.

If it is not a real typographic error, the user will answer some questions about the token: such as whether it is an url, an e-mail, a punctuation mark, a stop word, what its part of speech is and what its lemma is. Then, this information is appended to the *corrections* list and ask the user whether this information is stored in *Correction* collection for the future or in *SessionTypeError* collection for this session.

Once the detected word is managed, the *Analyser* resends the message to the typographic correction module in order to go on correcting it.

4.7. Execution behaviour

After executing it with the Gmail account that is going to be analysed (the author's Gmail account), of the 1084 e-mails extracted, 921 were measured, which represents approximately the 84.96% of the total. In this execution, all the 1084 messages were correctly preprocessed, but 163 were discarded in the typographic correction phase. Some of them were discarded because, after the preprocessing, they were missing text, whereas the rest of them did not pass this phase due to its language (there were e-mails written in English) or, a minority because they had a not interested message body for the analysis of the writing style (for example we found some e-mails whose only text was an url).

Chapter 5

Style feature analysis

""Data! data! data!" he cried impatiently. "I can't make bricks without clay.""
— The adventure of the Copper Beeches
Arthur Conan Doyle (1892)

Of all the style metrics used, our goal is to determine which ones vary and differ depending on the recipient of the message. With this in mind, in this chapter we are going to analyse the resulting values of measuring each message with the previously explained system.

The first step in our analysis is to prepare the data. We have to categorise the different contacts depending on their relationship with the sender, choose the features that we are going to study and modify its values in order to have the data ready for being analysed. All of this is explained in Section 5.1.

Once we have a defined the classification of each message, we are going to carry out a preliminary analysis of the style descriptors considered using clustering techniques (see Section 5.2). This study will reveal us how our different categories will fit with the clusters given by these methods.

As we will see, due to the big amount of style metrics, to describe the features and the different categories of contacts will be too difficult. For this reason, a dimension reduction will be required. There is a wide variety of dimension reduction techniques, but we are going to start with the most popular of them: Principal Component Analysis (see Section 5.3). With this method, we will obtain results that does not take into account our categories. In addition to it, each category will not be well balanced. For these reasons, it will be necessary to use a less common dimension reduction technique: Gini Importance of Decision Trees (see Section 5.4). After the application of this machine learning method, the system is going to be reduced to only eight dimensions.

Finally, we will repeat the analysis with clustering techniques, but this time with the obtained eight dimensions (see Section 5.5).

5.1. Data preparation: e-mail classification, metrics choice and correlation analysis

First of all it is necessary to classify the different recipients of the analysed messages. For this purpose, all the contacts (a total of 337 different e-mail addresses) have been

divided into twelve categories depending on their relationship with the analysed user. These categories are: *friend*, *acquaintance*, *company* (in this category are grouped all the company contacts with which the user has had a relationship to contract their service), *university*, *boss*, *colleague*, *professor*, *relative*, *stranger*, *university position*, *casting* (the people with which the user was in touch in order to manage a theatre casting belong to this relationship type) and *company recruiting* (where are classified the e-mail addresses that the user contacted to be a candidate in a recruiting process).

Our style markers were applied to each message, so it is necessary to categorise the different e-mails. With this in mind, we will determine the category of the message depending on its recipient(s). Classifying e-mails destined for a single e-mail account is a trivial problem (its category will be the one assigned to the message's recipient). We can also directly classify those messages whose recipients all belong to the same category. E-mails that have several receivers from different categories are automatically classified when they have only one addressee in the recipients field *To* (they are grouped in that contact's category), which represents the main recipient(s) of the message, while the *Cc* (Carbon Copy) and *Bcc* (Blind Carbon Copy) fields have the purpose of keeping the addressees in there informed. Otherwise, we classify it one by one (there were only 14 messages out of 921 that we had to review) depending on the type of relationship we think indicates the wording of the message.

After this classification process, we obtained the distribution of relationship categories that we can see in Figure 5.1. As we can observe, we have not equally distributed classes and this will represent a problem in our data analysis. Indeed, the biggest class (the *professor* class) represents approximately 39.41% of the total, while the second one (*university position*) in size is the 13.25%. And, of course, both categories are far from the smallest class (*acquaintance*) which only represents approximately 0.33%. Despite this unbalanced distribution between the different categories, we are going to analyse this data set and obtain conclusions in order to detect the most significant features for differentiating the writing style based on the recipient of the e-mail. We have to take into account that the conclusions will be closely linked to the data obtained given the small sample size.

Once all e-mails are classified in our twelve categories, we have to choose which style features we are going to analyse. At first glance, there are features of each message (the attributes of the *Metrics* class, which can be looked up in Section 4.5) from which we are not be able to extract significant numerical information, such as the sender of the e-mails (which is the same for all of them), the subject and the identifier of the thread they belong to (called *threadId*). Besides, as the distribution of the different categories is too unbalanced, we risk losing underrepresented classes if a time-related weight is applied over the several metrics. For this reason, we decide not to take the date into account for our analysis.

In addition to the mentioned features, we have removed from our data set the following writing style markers: *metricsSentences*, *wordLength*, *sentLength*, *sentNumWords* and *wordsAppearance*. All of them describe a distribution of a style feature (or several as the *metricsSentence* attribute) through a dictionary or list structure, which are excessively complex to manipulate with the rest of the style features using common machine learning techniques. Furthermore, they would produce a big amount of NaN (Not a Number) values in our data set, because of the diversity in the number of sentences and words used in each e-mail (for instance if a message has an only sentence, all the style metrics related to the subsequent sentences will have a NaN value).

Therefore, we are going to work with 27 writing style markers, the depth of the message (perhaps we can find significant conclusions with this parameter) and the identifier of each

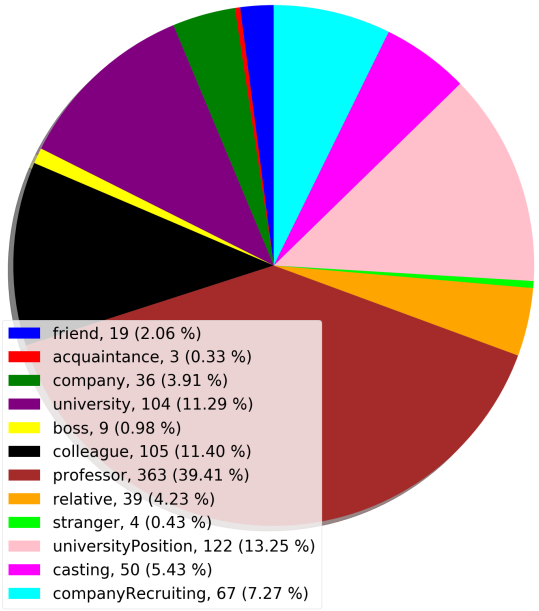


Figure 5.1: Distribution of relationship categories

message as index of each of the rows of our data set.

E-mail messages, by nature, do not contain a constant number of words from message to message. To overcome this variable and now that we have decided the style characteristics that we are going to study, the features are normalized, because techniques that require it (such as the K-Means algorithm) are used. Besides, we are going to find some NaN values, for example in *verbAdjectiveRatio* and *detPronRatio* in the messages where there are not adjectives or pronouns, respectively. The solution to overcome this problem, due to some algorithms do not admit data set with this type of values, is to assign the value of the arithmetic mean in the sample of individuals in the category to which the message belongs of the style marker in question, when it will be necessary. In other words, if an e-mail of the category C has a NaN value in the style metric M, it will be replaced by the value of the arithmetic mean of the feature M of the rest of the messages of class C.

It would be desirable to be able to visualize the main descriptive statistics to get an idea of each of the metrics. Nevertheless, given the big amount of style markers, the visualization becomes very complicated. For this reason, in this chapter, we are going to try to reduce the dimensionality of the system in order to be able to explain the main characteristics and describe the writing style.

Before starting with the data analysis, we are going to study the relationship between each selected feature. To carry it out, the Pearson correlation coefficient (Benesty et al., 2009) is going to be calculated between each pair of style markers. It is a measure of linear dependence between two quantitative random variables. Unlike covariance, Pearson's correlation is independent of the scale of measurement of the variables. Less formally, we can define Pearson's correlation coefficient as an index that can be used to measure the degree of relationship of two variables as long as both are quantitative and continuous. It has a value between -1 and $+1$, where 1 is total positive linear correlation, 0 is no linear correlation, and -1 is total negative linear correlation.

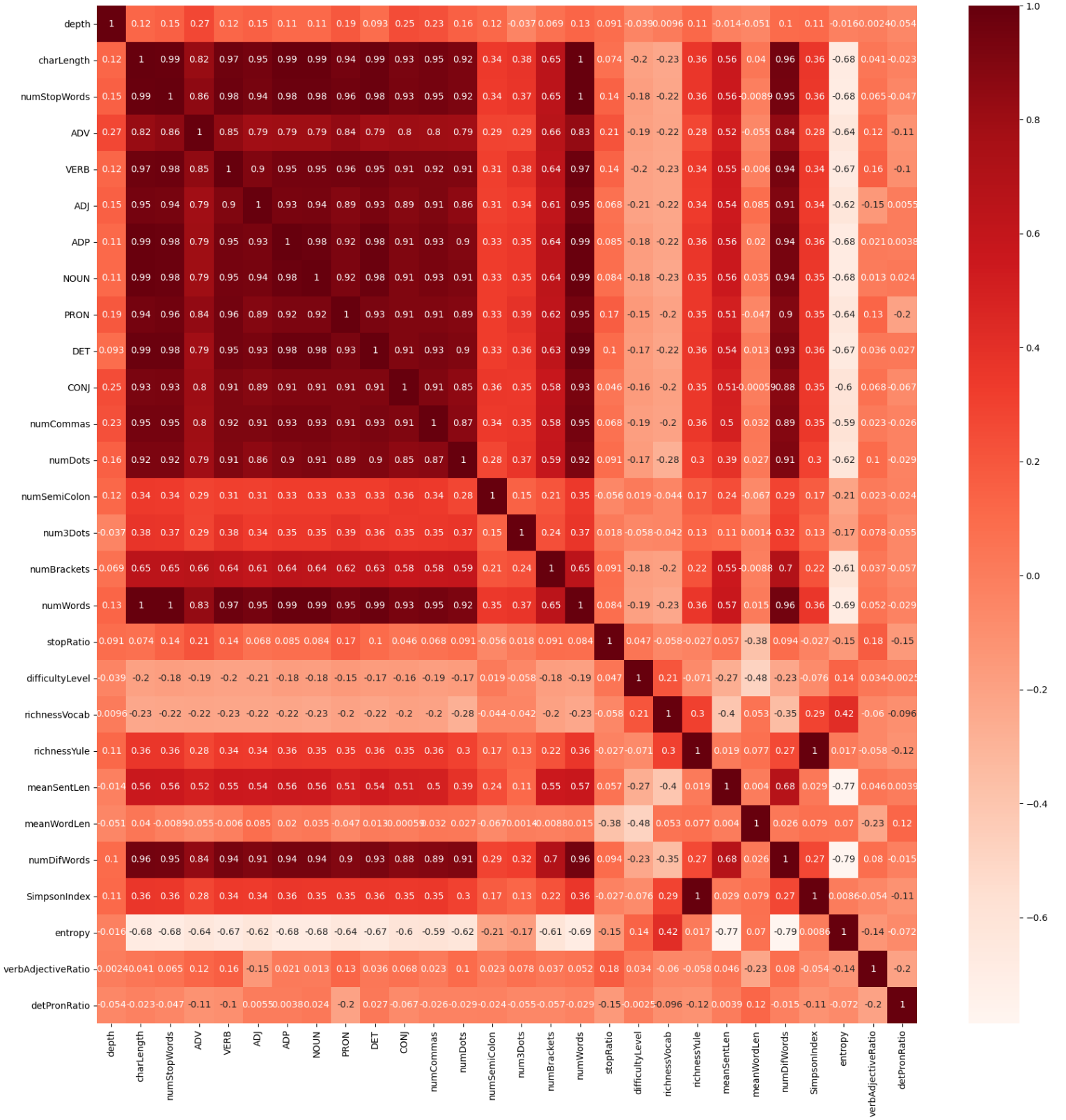


Figure 5.2: Pearson correlation coefficient between each pair of features

As a result of the calculation of the Pearson correlation coefficient, we obtain the heat map of the Figure 5.2. Logically, there is a positive linear correlation between those metrics that are strongly influenced by the length of the message. These pairs of style markers represent almost all results obtained close to the value 1. Moreover, there is a total positive linear correlation between Yule's Characteristic and Simpson's Index, which was predictable given the definition of one style feature with respect to the other (see Section 4.5.3). These relationship will be taken into account during the analysis of the data.

5.2. Preliminary analysis of the metrics considered using clustering techniques

In an initial approach, we are interested in knowing how well metrics fit our twelve category classification. To achieve this, we have executed two popular clustering algorithms which are going to group our set of elements (composed of the different style features) in such a way that members of the same group (called a cluster) are more similar in one way or another. These algorithms are K-Means (Hartigan, 1975) and DBSCAN (Ester et al., 1996).

Both algorithms require a parameter (in the case of K-Means the parameter is the number of clusters and in the case of DBSCAN the threshold distance that determines a neighbourhood of elements) which has to be defined before their execution. To make the decision of the initial value of the parameter there are methods based on the internal and cluster dispersion obtained. For this purpose, measures are taken to help the decision, such as the Silhouette Coefficient (Rousseeuw, 1987). It is a method of interpretation and validation of consistency within clusters of data. The technique provides a succinct graphical representation of how well each object has been classified. The best value is 1 and the worst value is -1. Values near 0 indicate overlapping clusters. Negative values generally indicate that a sample has been assigned to the wrong cluster, as a different cluster is more similar. Likewise, we can obtain a general idea of the behaviour of the clustering by calculating the mean Silhouette Coefficient for all samples.

Furthermore, we need to assess how much our classification resembles the clusters obtained after the execution of each of the algorithms. For this evaluation, we can use the Adjusted Rand Index, which is a form of the Rand index (Rand, 1971) that conforms to the random grouping of elements. The Adjusted Rand index is thus ensured to have a value close to 0.0 for random labelling independently of the number of clusters and samples and exactly 1.0 when the clusterings are identical (up to a permutation).

Due to the presence of NaN values, we are not able to use the K-Means algorithm directly on the data. Instead of replacing the NaN values as we have explained in Section 5.1, we are going to use a slight variation from the K-POD algorithm (Chi et al., 2016), which runs K-Means iteratively while it modifies the cells where the value is missing by assigning the value of the centroids. The algorithm that we are going to use, similar to the K-POD, is the one shown in Algorithm 1, where we have two invoked functions. The first one is *mean*, which returns the mean of the given array without taking into account the missing values. The second one, *KMeans*, is a function that applies the K-Means algorithm given a set of initial centroids (or it will generate them randomly), the number of clusters and the dataset. It returns an array as long as the number of rows of the given dataset which indicates the cluster index (through an integer) that each element belongs to and the coordinates (features values) of the centroid of each cluster (it will be a matrix with

Algorithm 1 K-Means with missing values

INPUT: Data set X (represented as a matrix whose columns are the features and whose rows are the different samples) with missing values, number of clusters k and the maximum number of iterations to perform $maxiter$.

OUTPUT: A vector $labels$ that indicates to which cluster each element belongs and a data set X' which is a copy of X with the missing values filled in.

1: $X' = X$
2: $missing$ = list of positions (pair of rows and columns) of the missing values of X
3: **for** $(row, column)$ in $missing$ **do**
4: $\quad X'[row, column] = mean(X[, column])$
5: **end for**
6: $i = 1$
7: $converge =$ **false**
8: $prevlabels, prevcentroids = KMeans(init = random, k, X')$
9: **for** $(row, column)$ in $missing$ **do**
10: $\quad X'[row, column] = prevcentroids[prevlabels[row]][column]$
11: **end for**
12: **while** $i < maxiter \wedge \neg converge$ **do**
13: $\quad labels, centroids = KMeans(init = prevlabels, k, X')$
14: $\quad$ **for** $(row, column)$ in $missing$ **do**
15: $\quad\quad X'[row, column] = centroids[labels[row]][column]$
16: $\quad$ **end for**
17: $\quad converge = (prevlabels == labels)$
18: $\quad$ **if** $\neg converge$ **then**
19: $\quad\quad prevlabels = labels$
20: $\quad\quad prevcentroids = centroids$
21: $\quad\quad i = i + 1$
22: $\quad$ **end if**
23: **end while**
24: **return** $labels, X'$

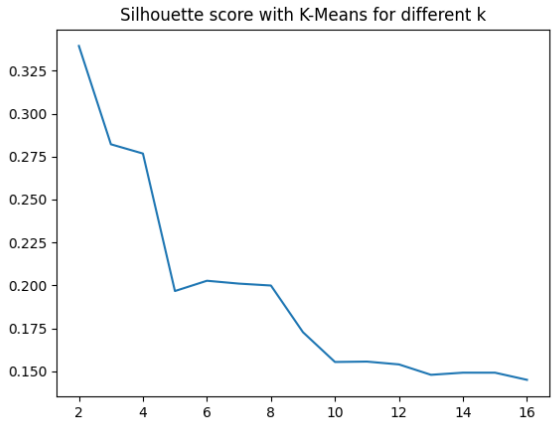


Figure 5.3: Silhouette Score with K-Means for different k

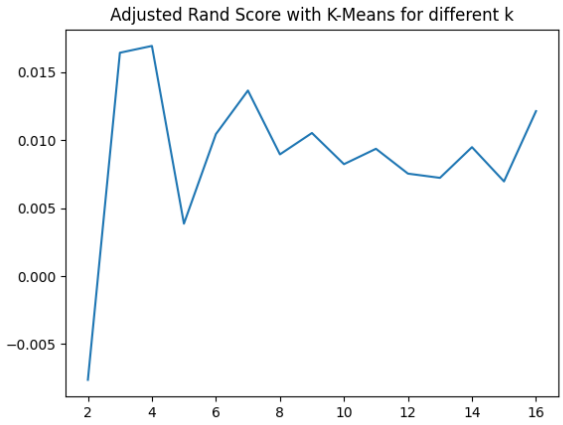


Figure 5.4: Adjusted Rand Index with K-Means for different k

as many rows as the number of cluster and as many columns as the numbers of features).

Now that we have chosen the algorithm, we execute it with different k parameter (the number of clusters). The rest of the input will be the normalised data with the NaN values and with a maximum of 100 iteration. With each k-dependent execution, we will calculate the Silhouette Score (which is the mean of the Silhouette Coefficient of all samples) and the Adjusted Rand Index given the real classification. As a result of this we obtain Figures 5.3 and 5.4.

In respect of the Silhouette Score analysis (which is shown in Figure 5.3), with the given values, we are able to claim that, in general, as the number of groups increases the Silhouette Score decreases. This fact indicates us that the best number of clusters in order to achieve a good differentiation between each group of elements is two, which is not in line with our classification model. Not surprisingly, these results, which do not fit well in the established categories, are accompanied by poor values of the Adjusted Rand Index. As we can observe in Figure 5.4, all the obtained values with any number of cluster is very close to zero, which means, as we have previously explained, that the obtained classification does not match with ours.

In the case of DBSCAN algorithm, we are going to replace the missing values as we have explained in Section 5.1. This clustering technique needs two different parameters: the threshold distance that determines a neighbourhood of elements (denoted by ε) and the minimum number of elements that forms a cluster. We will assign the value of three to this last parameter. This choice is motivated by the distribution between the different categories that we have previously defined. As we can observe in Figure 5.1, the smallest class has three elements in it, so it would not be consistent with our classification if a minimum number bigger than three is established. Moreover, the value of one does not make sense, since all the points of your data set will be a cluster (we would lose the possibility of detecting noise which is one of the advantages of DBSCAN over K-Means), and with 2 the result will be the same as the hierarchical cluster (Nielsen, 2016) with the single-link metric, with the cut at the height of the dendrogram ε.

As we have done with K-Means, we are going to execute the DBSCAN algorithm with different ε parameters. Besides, both the euclidean and manhattan metric are going to be used for this analysis. However, we will get similar results in both cases, so we are going to present the values obtained with the euclidean metric (see Figure 5.5).

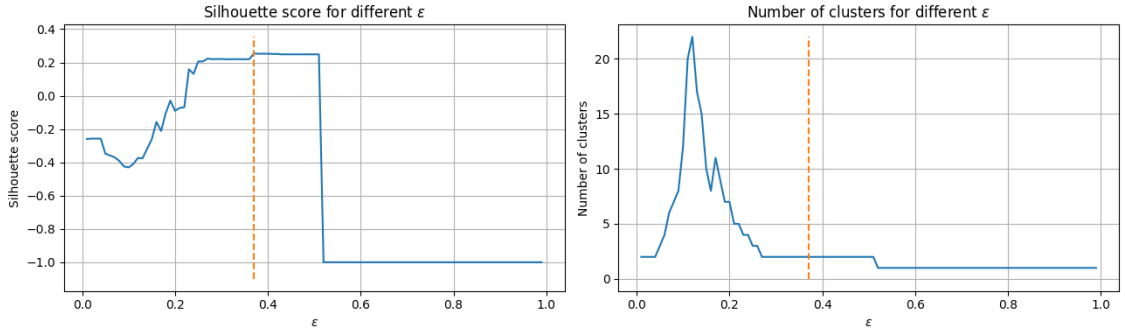


Figure 5.5: Results of DBSCAN execution with euclidean metric

As in the case of the K-Means algorithm, we can find the maximum Silhouette Score with two clusters, which is not in line with our classification model. Furthermore, as we can see in Figure 5.6, we find again values very close to zero in the Adjusted Rand Index analysis.

In conclusion, using the clustering techniques to classify the messages according to the selected metrics, as expected, we do not obtain significant results that fit our model or allow us to group the different e-mails in another way. One of the problems found to achieve this is the great amount of states that each element has, that is, the high number of dimensions of the system. We also find this inconvenience when we try to get the main statistics of the different features that describe the messages. Therefore, it is an issue that must be addressed (the reduction of dimensionality), especially trying that this reduction serves to adapt to the categorization carried out or to obtain a smaller number of parameters that define the writing style.

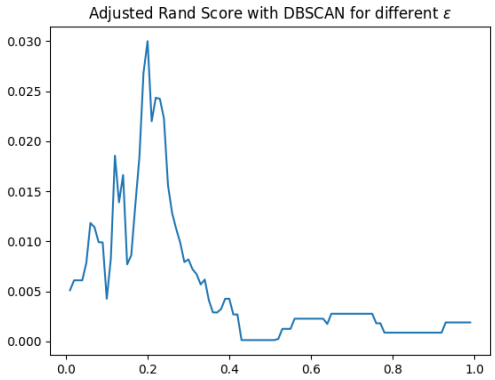


Figure 5.6: Adjusted Rand Index of DBSCAN with euclidean metric

5.3. Dimension reduction using Principal Component Analysis

In statistics, principal component analysis (PCA) is a technique used to describe a data set in terms of new, uncorrelated variables (components). Components are ordered by the amount of original variance they describe, so the technique is useful for reducing the dimensionality of a data set. Each of them is a linear combination of the set of features of

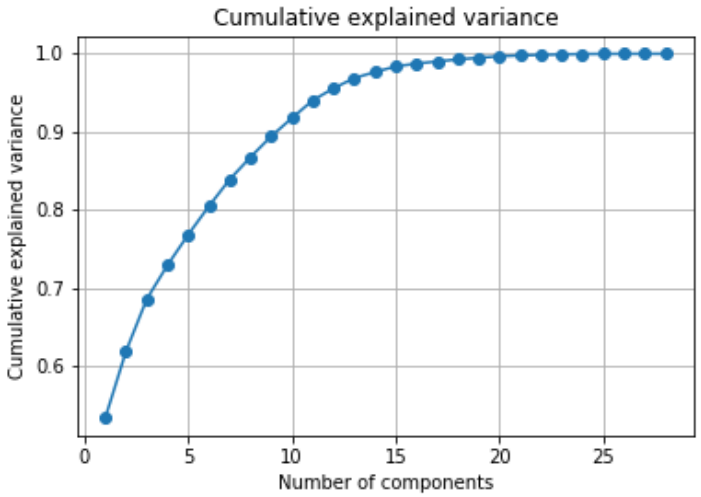


Figure 5.7: Evolution of cumulative explained variance ratio

the system. Therefore, if we know the weight assigned to each characteristic of the system, we are able to deduce the "importance" of each feature weighted by an specific explained variance.

For the PCA, the normalized data will not be enough. Of course, it will be necessary to replace the missing values as we explained in Section 5.1, but also we are going to require a set of data with its features centred in zero, that is to say, that their mean must be zero. This transformation is called standardisation and we will apply it to our dataset.

If the PCA is executed with as many components as features, the sum of the explained cumulative variance ratio of all components is always 1. In other words, if all the main components of a dataset are calculated, then, although transformed, all the information present in the original data is being stored. With this method, we are able to know the various components that we can obtain and their explained variance. Likewise, the behaviour of the cumulative variance ratio is defined by the curve shown in Figure 5.7.

Looking at Figure 5.7, we can affirm that around the 10 components, the increase of the explained accumulated variance stops being substantial and we reach a reasonable value of it. Hence, with the observed curve we are able to determine the suitable number of components. However, before delving into each of the components, let's study in more detail the distribution of the variance explained. For this purpose, we are going to represent the distribution of explained variance in a pie chart with which it will be easier for us to compare the different values of it. This graph is shown in Figure 5.8.

Taking advantage of the information provided by the last graphic (Figure 5.8) we can observe that the only component that has an explained variance ratio bigger than 10% is the first one. Besides, from the fourth one all of them has a value smaller than 5% and from the thirteenth one the components have a poorly significant value. Nevertheless, we have to take into account that, given the distribution of our classification (see Figure 5.1), the losing of a small percentage of explained variance may mean missing information related to categories with few elements. This results from the fact that the PCA does not consider the appropriate classification during its execution.

In spite of the explained results in terms of components distribution, we could expect to obtain more clarifying values in the weights that define the components with higher explained variance ratio. Therefore, we will now know the linear combination of the first

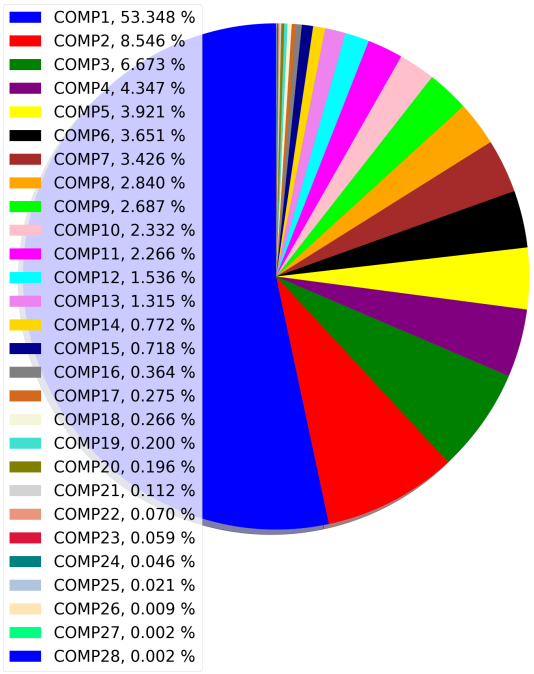


Figure 5.8: Distribution of explained variance ratio

component with respect to the characteristics explained.

The best way to visualise the different linear combination weights is through a pie chart. This is because, with this graph, it is easy to compare the importance given to each dimension. In our Figure 5.9, we have striped each linear combination which has a a negative weight and represented the absolute values of all coefficient. Since we are not so interested in the sense of each dimension in the definition of the first component, we will calculate the direction ratio that is assigned to each characteristic, for example if our system had two features (which is the same as saying that the system has two dimensions) and the direction ratio was greater in the first one, which we can represent on the abscissa axis, we would obtain a vectorial component whose representation in the common Cartesian plane will be "more horizontal than vertical", since the weight assigned to that dimension is greater. To find this direction ratio, we will divide the absolute value of the coefficient by the sum of the absolute value of each of the weights, that is to say, if a component is defined as follows:

$$c_{i,k} = \sum_{j=0}^{N} \lambda_{i,j} x_{k,j}$$

Where $c_{i,k}$ is the value of the i-th component of the k-th e-mail, N is the number of dimensions (28 in our case), $\lambda_{i,j} \in \mathbb{R}$ is the linear combination coefficient (also called weight) of the i-th component for the j-th dimension and $x_{k,j}$ represents the j-th feature of the k-th message. Then, the direction ratio of the j-th characteristic of the i-th component is as follows:

$$d_j = \frac{|\lambda_{i,j}|}{\sum_{j=0}^{N} |\lambda_{i,j}|}$$

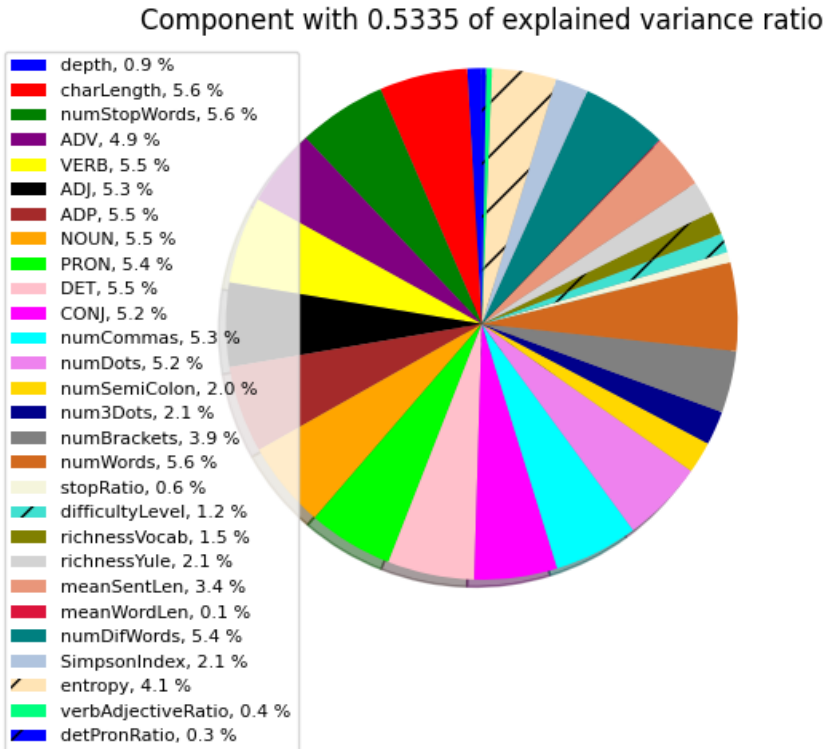


Figure 5.9: Linear combination that defines the first component

The result of this operation will be the percentages that we can find next to each characteristic in the Figure 5.9.

In addition to the problems of the choice about the number of components given our distribution in categories, we have a balanced assignment of weights of almost all the features in the first component, which has the highest explained variance with a ratio of 53.35%. These information does not allow us to determine which style markers differentiate the categories of the messages. Furthermore, by not taking into account our classification, we can only state that the assignment of coefficients of the linear combination that defines the first component distinguishes the elements of the set equally, regardless of the class to which they belong.

As the rest of the components have an explained variance ratio smaller that 0.1, their direction ratios will not be sufficiently representative to overcome such a balanced distribution. For this reason, we can conclude that it is necessary to look for other method of dimension reduction which provides us information taking into account our classification and allows us to know which style metrics describe the different categories in the best possible way.

5.4. Dimension reduction using Decision Trees

One method of machine learning, although not mainly used for dimensional reduction, that takes into account a given classification are Decision Trees (there are some researchers that have studied the feature selection using them as Sugumaran et al. (2007) and Cho and Kurup (2011)). A Decision Tree (Rokach and Maimon, 2008) is a prediction model which, given a set of data, makes logical construction diagrams, very similar to rule-based

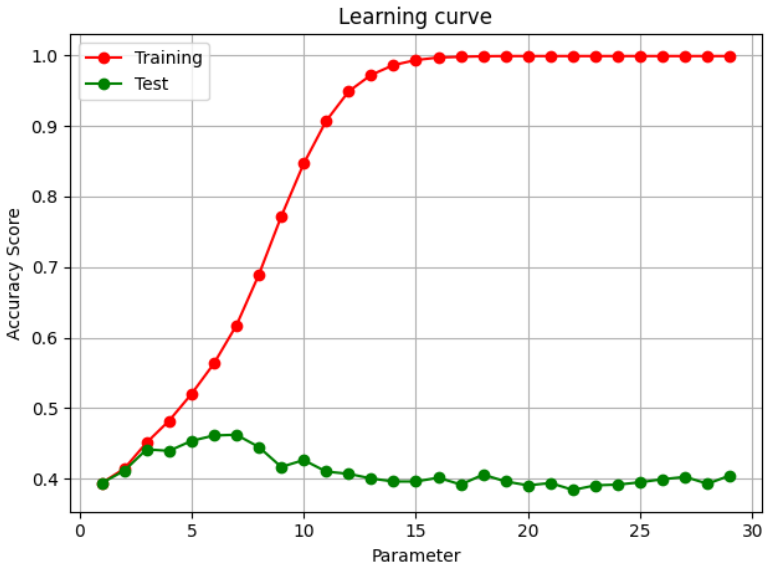


Figure 5.10: Learning curve with the 28 chosen features

prediction systems. These diagrams serve to represent and categorize a series of conditions that occur successively for the resolution of a problem. There are many algorithms to implement them. We are going to use an optimised version of the CART algorithm (Breiman et al., 1984) with entropy as its criterion.

The advantages of Decision Trees are that they take into account the defined categorisation, as it is a supervised machine learning classification method, and that they are very explainable. However, our purpose is to know the features that best describe the writing style based on the recipient, instead of classifying new messages. For this reason, we are going to make use of the structure of the constructed Decision Tree in order to measure the importance that each style metric has in it.

A good intuition is to think that, in order to study the importance of a node, it is important to bear its depth in the tree in mind, because the lower it is, the more elements it differentiates. However, it will not be so useful if it just separates elements of the same class. Likewise, the number of samples that reach the node and its category is an important factor to keep in mind. Nevertheless, it will not be helpful if it maintains the proportion of each category in its child nodes. We are able to think of many parameters that can have relevance in the definition of the importance of a node in the Decision Tree. In this case we are going to use the Gini Importance (Breiman, 2001), which is defined by the following expression:

$$ni_j = w_j H_j - w_{left(j)} H_{left(j)} - w_{right(j)} H_{right(j)}$$

Where ni_j is the importance of node j, w_j is the weighted number of samples reaching node j, H_j is the entropy of node j, $left(j)$ is the child node from left split on node j and $right(j)$ is the child node from right split on node j. Consequently, the importance of each feature is defined by the following formula:

$$fi_i = \frac{\sum_{j \in Nod(i)} ni_j}{\sum_{j \in Nod} ni_j}$$

Where fi_i is the importance of feature i, $Nod(i)$ is the set of nodes which split on

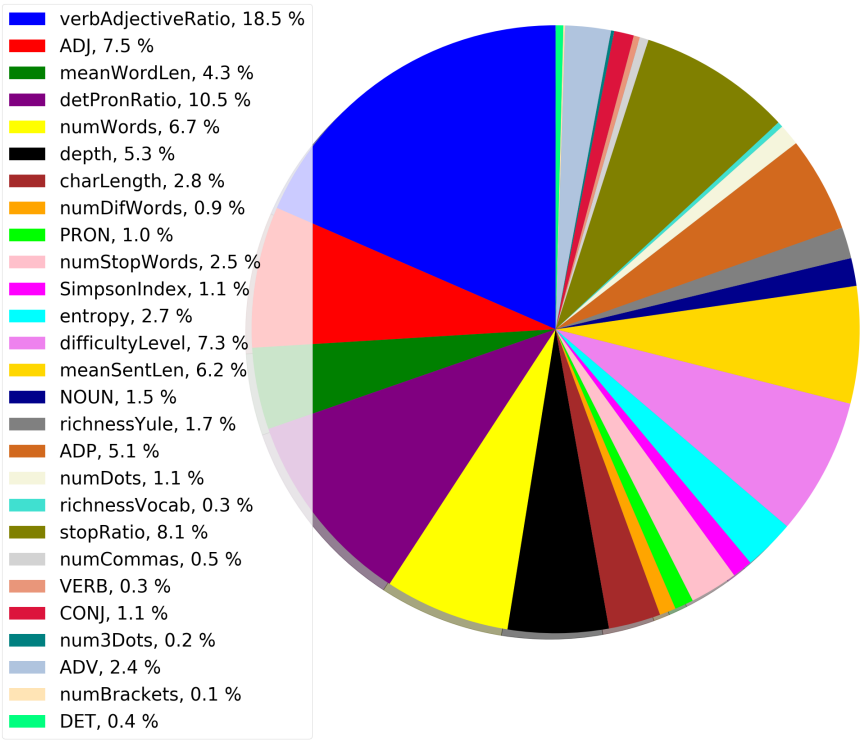


Figure 5.11: Distribution of normalised feature importance with 28 features

feature i and Nod is the set of all nodes. In our study we are going to use the normalised feature importance, which is defined by the following expression:

$$nfi_i = \frac{fi_i}{\sum_{j \in F} fi_j}$$

Where nfi_i is the normalised feature importance and F is the set of features. Once we have the expression required for the analysis of the importance of each feature, we are able to calculate the distribution of the importance of each style metric with our 28 chosen style markers. To build the Decision Tree, we have to decide the depth of it. To take this decision, we calculate the learning curve both in training set and test set, and obtain the curves that we can observe in Figure 5.10 (the normalised data was used for the calculation of learning curve, as well as in the construction of the Decision Tree). Thus, we will choose a depth that avoids the overlearning (which could be produced in values of depth with which the training accuracy score is 1) and the missing of information (depth with which the training accuracy score is less than 0.9). Our choice will be the depth whose training accuracy score is the interval $(0.9, 1)$ and its test accuracy score is maximum (in this case it is eleven, but later, when we had less features, it will follow this criteria).

Making use of the explained expressions for the calculation of the normalised feature importance, we can go through the created tree with the chosen depth in order to obtain the distribution of this value. The result is shown in Figure 5.11.

As we can observe, the *numSemiColon* characteristic does not appear in Figure 5.11, which means it has no importance in our constructed tree. Besides, *verbAdjectiveRatio*, *detPronRatio* and *stopRatio* have the highest importance ratio and their related metrics (*ADJ* and *VERB*, *DET* and *PRON*, and *numStopWords*, respectively) have a very small value. For this reason, we are able to claim that we can dispense with the related style

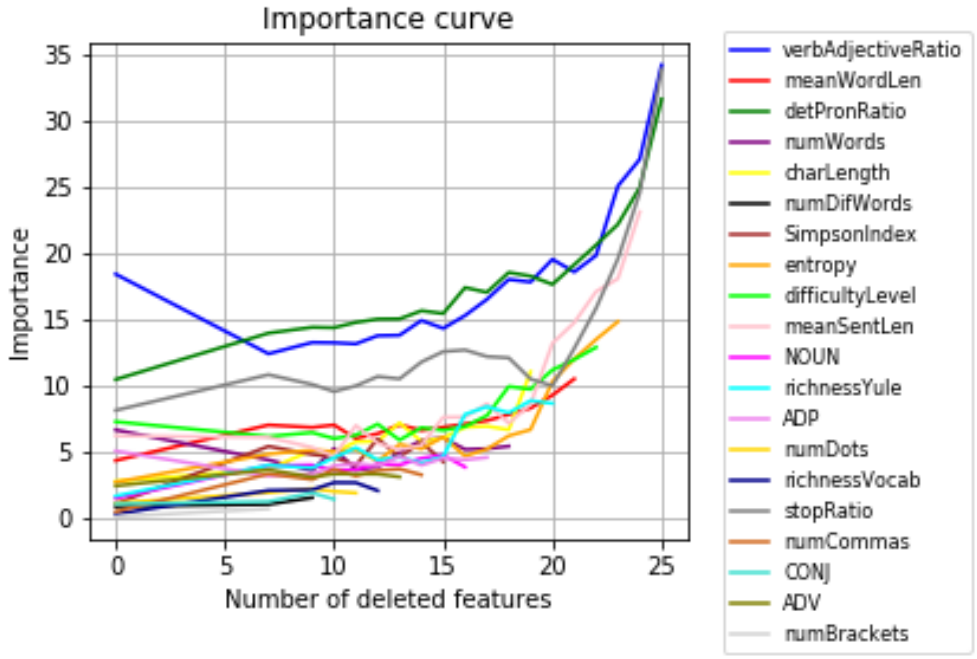


Figure 5.12: Evolution of importance ratio

features and *numSemiColon* in order to describe the writing style. Therefore, we can construct another Decision Tree (by automatically taking a depth, as we have explained before) to calculate the importance ratio of each of the non-removed style markers. When we have the distribution of Gini Importance, we can remove again the non-important style metrics and those that have an extremely low importance ratio. By repeating this process, we are able to choose a small number of features which have a big importance ratio in the classification of the messages based on their recipients.

The learning curves of these iteration are all very similar to the one shown in Figure 5.10. However, the evolution of the importance ratio of the style metrics is not uniform during all this iterative process. This behaviour could be seen in Figure 5.12.

Figure 5.12 represents the importance ratio of each feature until it was removed from the set of style markers. The features that does not appear in the legend are those that were non-important in the first or second iteration, or were removed (such as the previously mentioned *ADJ* and *VERB*) before the second step.

Before detailing the different importance curves of each feature, there are some interesting general observations. Until the elimination of twenty features, which means having eight style metrics, it is always decided to dispense with some style marker whose importance is around 5% compared to others that are above 10%. From this point on, we see that characteristics with a more relevant importance start to be lost. From this fact we can deduce that keeping eight style metrics is a good principle to describe the style based on the recipient.

In general, the behaviour of most of the features is constant. As we can observe, most of the last eight style markers were the most important features at the beginning of the process. Of course, little by little, some of the metrics experience an increase due to, as the sum of all the non-removed metrics importance is always the same, the ratio has to be distributed between a lower number of characteristics. However, this increase becomes remarkable as soon as a big amount of style markers has been deleted (approximately from

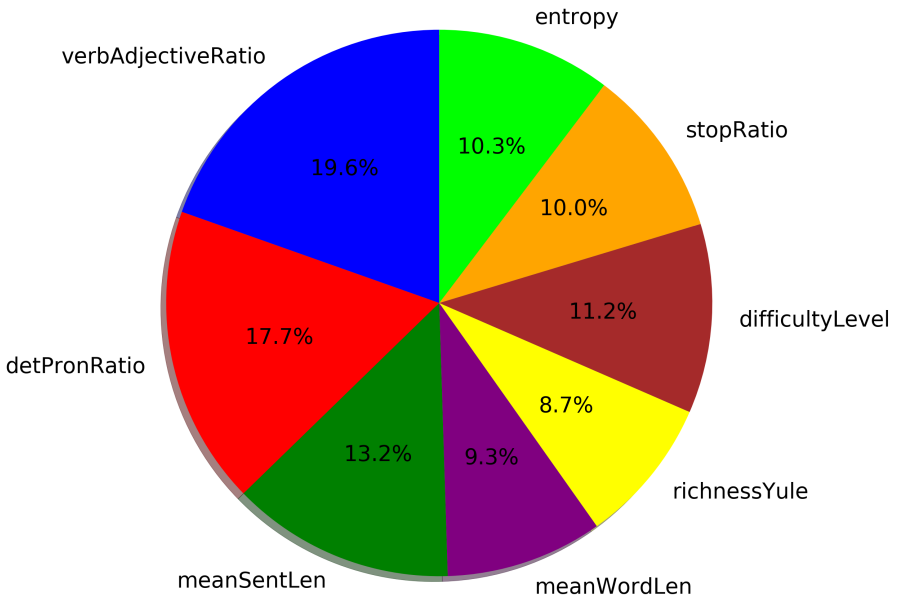


Figure 5.13: Distribution of normalised feature importance with 8 features

20 removed features).

Thanks to the constant evolution of the importance of each metric, we can claim that most of the selected features (those which had not been removed until the number twenty), were those which had the highest values at the beginning; as well as, almost all of the deleted style markers when they have insignificant values of the ratio, were unimportant at the beginning. This fact allows us to assert that, given our dataset, our classification and our selected features, to add unimportant style markers does not excessively contribute to hide the really significant style descriptors.

Another possible assessment of the evolution of importance described by the Figure 5.12 is that most of the features that are eliminated below 5% of importance, before being so experience a slight decrease.

Going into more detail, the last eight selected features are: *verbAdjectiveRatio*, *detPronRatio*, *meanSentLen*, *meanWordLen*, *richnessYule*, *difficultyLevel*, *stopRatio* and *entropy*. All of them have an importance bigger than 8% as we can see in the importance distribution of the Figure 5.13. Moreover, as we can check with Figure 5.2, none of these metrics are directly correlated with each other.

In respect of the removed descriptors, some of them were deleted because they are related with another metric with has a bigger normalised feature importance. This is the case of *ADJ*, *VERB* (both related with *verbAdjectiveRatio*), *DET*, *PRON* (this last two are related with *detPronRatio*), *numStopWords* (related with *stopRatio*) and *SimpsonIndex* (which is directly correlated with *richnessYule*, due to their definitions). The unimportant style markers were also removed. In this case we have only two examples: *numSemiColon* and *num3Dots*.

On the other hand, we have deleted some style metrics due to their very low importance ratio and the existence of another style marker with a bigger value which is correlated with them. *ADV*, *ADP*, *NOUN*, *CONJ*, *numCommas*, *numDots*, *numWords* and *numDifWords* belong to this circumstances. The *numBrackets* feature was removed only because of its extremely poor normalised feature importance (when it was deleted it had a value of 0.7%).

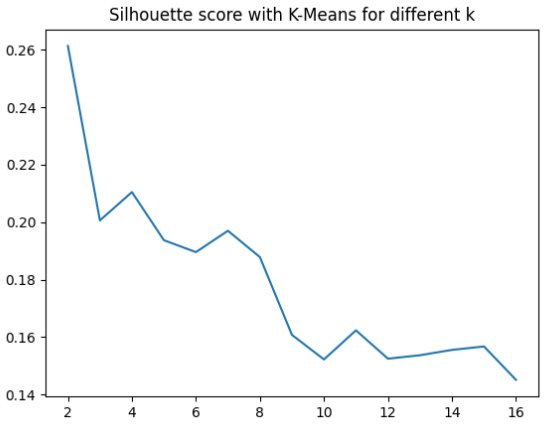


Figure 5.14: Silhouette Score with K-Means for different k

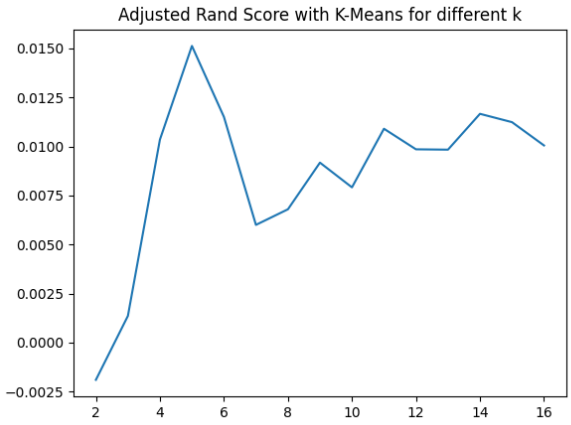


Figure 5.15: Adjusted Rand Index with K-Means for different k

We still have to explain the reasons why three style descriptors were eliminated. The *depth* feature was removed because our purpose in this work is to develop a model which is based on the recipient of the message and not on its depth. Perhaps, it is possible to obtain characteristics of a message related to this style marker, for instance the length of the message, but this is not the goal of this work. The case of the elimination of *richnessVocab* is due to its similarity to the *richnessYule*, but less complexity and a very low normalised feature importance. Finally, we can also find similarities between *charLenght* and *meanSentLen* and *meanWordLen*, which caused the first one to be eliminated.

In conclusion, thanks to the Gini Importance, we were able to measure how significant a metric is in conforming to the initially defined categorisation. This results from the nature of Decision Trees which are an easily explainable classification method. Hence we have selected eight different style markers which describes the writing style based on the recipient of the e-mail.

5.5. Analysis of the chosen metrics using clustering techniques

As in Section 5.2 we studied the coincidences of our classification with that generated by clustering algorithms, we will carry out the same analysis but only with the eight metrics chosen in Section 5.4.

Starting with the algorithm K-Means with missing values (see Algorithm 1), we will execute it with different number of clusters, which is the parameter needed by the algorithm. Then, we are going to calculate both the Silhouette Score of each execution and the Adjusted Rand Index. Likewise, we are able to evaluate the classification done with regard to our categorisation. The result of all this process can be see in Figures 5.14 and 5.15.

Analysing Figure 5.14, which show us the Silhouette Score for different numbers of clusters, we can observe that its result is very similar to the one represented by Figure 5.3. As in that case, the best Silhouette Score is obtained when the parameter has the value two. However, this result is far from our classification which has twelve different categories (these were defined Section 5.1). This Silhouette Score means that more than two clusters

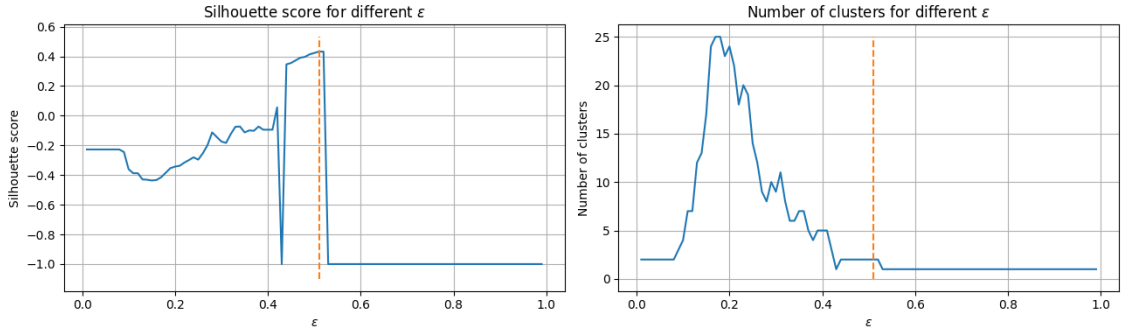


Figure 5.16: Results of DBSCAN execution with manhattan metric

do not differentiate well enough.

To check how the resulting classification fits with our categorisation, we use the Adjusted Rand Index (as it is described in Figure 5.15). However, the best result that we are able to obtain is with five cluster and its Adjusted Rand Index is around 0.015. As we know, it is a value very close to zero, what means that there are not enough coincidences in the resulting classification and our categorisation. The rest of the values with other numbers of cluster are worst than this.

After this unfortunate results, we are going to carry out the analysis with DBSCAN algorithm. As we have explained, DBSCAN requires a threshold distance and a minimum number of elements that can create a cluster as parameters. As in Section 5.2, we are going to assign the value of three to this last parameter and to execute with different ε values (the threshold distance) for the analysis. Furthermore, as it is possible to execute it with different metrics we are going to try with both euclidean and manhattan distance. Then, the Silhouette Score and Adjusted Rand Index of each execution are calculated.

The results of the Silhouette Score calculation with both metrics is very similar. For this reason, we will only show the one with the manhattan distance (see Figure 5.16). In the graph which represent the different Silhouette Score values depending on the taken ε, we are able to see that the maximum value is obtained with a threshold distance that creates two different clusters. As with the K-Means algorithm, this indicates that the best differentiating classification is very far from our categorisation. Once we have observed the same result with these two algorithms, we can claim that our different categories are not different enough for the clustering algorithms with the eight selected dimensions.

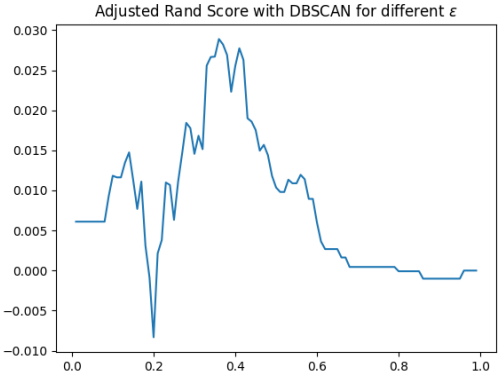


Figure 5.17: Adjusted Rand Index of DBSCAN with manhattan metric

As expected, the results of the Adjusted Rand Index are very close to zero again. It can be observed in Figure 5.17. The higher Adjusted Rand Index does not achieve the value of 0.03 and the rest of the values are smaller than it. This means that our categorisation does not fit with the returned classification.

In conclusion, the two clustering techniques that we have used for analysing the data with the selected eight dimension do not return a classification similar to that defined by us. However, the results with all features were not initially promising. It could mean that the implemented style markers are not good enough in order to describe the style based on the recipient. Nevertheless, it would be necessary a research with a bigger amount of messages to say that and, perhaps, with a more balanced distribution of each category.

Chapter 6

Proposal for a personalised writing model based on the recipient

"Science may never come up with a better office communication system than the coffee break"
— Earl Wilson

After analysing the metrics that define the style of the e-mails based on its recipient, we are able to design a system that takes advantage of this knowledge and generates messages according to what we learnt. In this chapter we will explain a proposal for this system with which the user can obtain a text just by providing some keywords related with the topic of the desired e-mail and its recipient. With this in mind, we are going to detail the different phases of our model and its general architecture (see Section 6.1). Then, each one of its tasks are going to be explained: searching phase (see Section 6.2) and rewriting phase (see Section 6.3).

6.1. Phases of the model

Based on the work done, we will propose a model for generating personalised messages based on the recipient. However, before detailing the model proposal, we must make some observations.

Firstly it is necessary to underline that the obtained results are highly dependent on the initial data, the aggregate of which is not sufficiently large for the conclusions to be representative. Moreover, the categorisation is too unbalanced. All this must be taken into account, since our model will be based on these results.

Besides, we will reuse the implementation developed (see Chapter 4) for our model, as well as extend its functionality to areas other than research such as software application development. This is because the model can be used for automatic e-mail generation among other purposes, and its design will depend on the purpose for which it is developed.

As we can see in Figure 6.1, one of the required inputs of our system is the set of evaluated e-mail style metrics. Therefore it will be necessary to make use of the Analyser developed. As we have underlined, the modification of the given implementation depends on the purpose. It would be possible to remove the typographic correction phase if we want to develop a software aimed to be used by users (they will not have a good user experience if they have to correct their own e-mails before they can use the application) or if we want to take into account the typographic errors of the user with a new style marker. However,

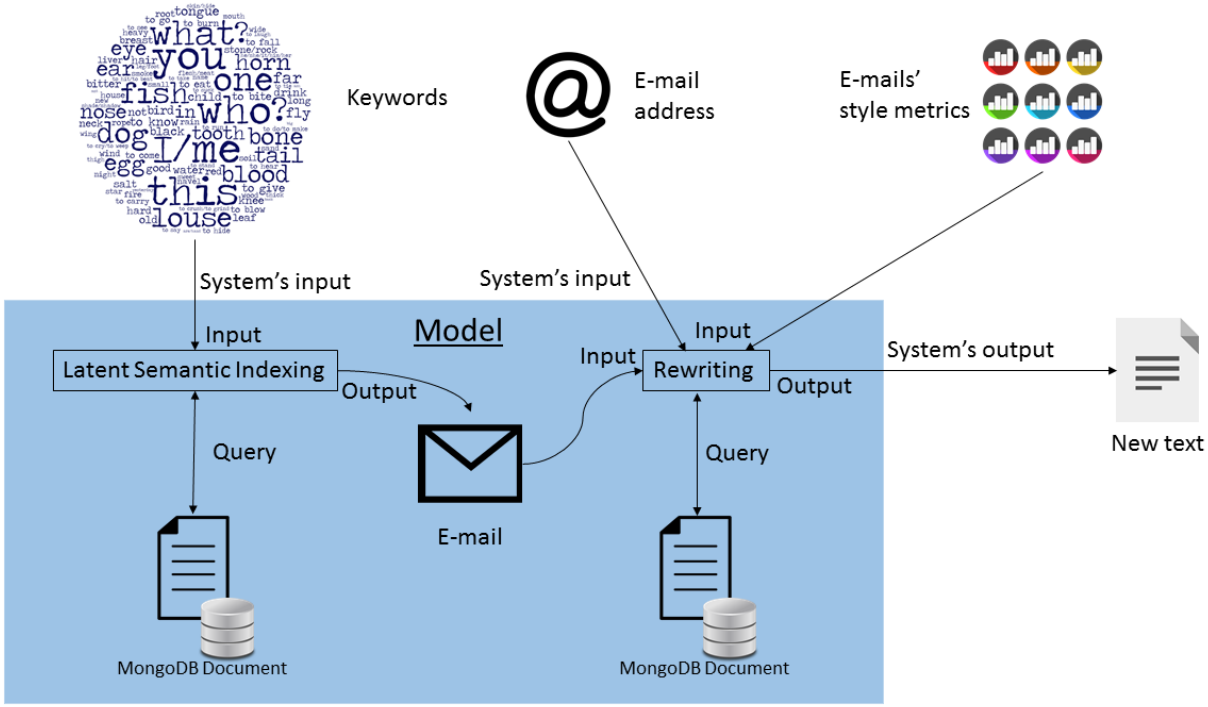


Figure 6.1: Model Architecture Diagram

and thanks to the way the Style Analyser was implemented (with different modules as web services), any little or big modification in a module will not affect the rest of the phases. This will facilitate the reuse of the implementation developed. In this Section, we will not delve into it, instead we will just propose the model once the calculation of the different metrics is done.

Instead of trying to generate a complete e-mail, the basic idea of our model will be to rewrite one already written by the user. To achieve this, we design a model based on two phases: searching (its details are explained in Section 6.2) and rewriting (see Section 6.3).

The searching phase is in charge of looking for a previously written message given a set of keywords. With this in mind, we can take advantage of the typographic corrected stored e-mails (or the preprocessed messages if this module is not used) to carry out the search. The only input that this module needs is the mentioned set of keywords, and its output is the text of the message written by the user.

The rewriting phase receives the output of the searching module. However, it will require more information in order to modify the text. For this reason, it is necessary to know who is going to be the recipient of the message and the results of the calculation of the style metrics. Once we know it, we can query the database where the classification of the different contacts is stored and, with this information, we are able to categorise the given contact. Its category will allow us to know the values of the style metrics of it and, with this information, we can choose the different methods to modify the e-mail. The output of the rewriting phase will be the new text of the message.

After having this brief introduction to the two different phases of our model, we can clearly know its inputs and outputs. At least it will be necessary to receive as input a set of keywords that describe the content of the message to be generated and its recipient. Thus, we have in our system a communicative goal (which describes the topic of the text to be

generated) and a user model (which consists of the categorisation of the recipient of the message), which are the set of keywords and the e-mail address, respectively. In addition we must have the style metrics previously calculated (which are part of our information about the user, that is to say, belong to our user model) and the databases that store the texts of the messages (which is our knowledge source, that is to say, information about the domain) and the established classification. Therefore, following the scheme proposed by Reiter and Dale (2000), our natural language generation system has a knowledge source, communicative goal and a user model, but it has not a discourse system (a model of what has been said in the text produced so far). In reality, we have it in the previous messages exchanged between the user and the recipient, but we are not taking into account for this model.

In respect of the output, it will be the generated text which is going to be the body of the e-mail sent to the given contact. Below we will detail each of the two phases that make up our system.

6.2. Searching for the e-mail with the most similarity

Searching phase is in charge of finding the message in which the given set of keywords has the most weight. As we have studied in Section 2.3, a good method used for this type of purposes is Latent Semantic Indexing. With it, we not only take into account the most significant words (eliminating stop words) but also, thanks to the Singular Value Decomposition (see Section 2.3.2), we achieve a relationship between the term and the concept it represents, that is, we are able to face semantic problems in the consultation of documents such as synonymy that produce irrelevant results in methods such as boolean keyword queries. In fact, several researchers, such as Landauer et al. (1998), have shown that there is a significant correlation between the way humans and LSI process different documents. Other researchers, such as Bartell et al. (1992) and Ding (1999), have demonstrated that LSI is a useful solution for conceptual matching problems.

However, LSI is a technique that requires a lot of memory and processing power. Both the generation of TF-IDF table (see Section 2.3.1) and the truncation of the singular value matrix have an expensive algorithmic complexity. To alleviate this problem it is possible to pre-calculate both TF-IDF table and the truncation of the singular values matrix. This way, when the user performs a query it is only necessary to read from a file the result of these operations.

In order to calculate the TF-IDF table, we need to access the database where we store the last version of the messages from which the different metrics have been extracted. It will be necessary to analyse each of the different e-mails stored. To obtain the different TF-IDF vectors it is recommended to use the most frequent expression (as Tang et al. (2014) claim) to find this value given a t term in a d document of the D document collection:

$$tfidf(t,d,D) = \frac{f(t,d)}{\max\{f(t,d) : t \in d\}} \cdot \log\left(\frac{|D|}{|\{d \in D : t \in d\}| + 1}\right)$$

Once we have the table, we calculate its Singular Value Decomposition and truncate the singular value matrix to reduce its size and achieve the semantic relationships between the terms we are looking for (as it is explained in Section 2.3.2).

Finally, we will take the input given by the user as keywords to generate the text message and make a query comparing the similarity between each message and the words provided by the user (as we have explained in Section 2.3.3). The output of the system

will be the e-mail with the most similarity with all its information as the recipient and body of the message.

6.3. Transforming e-mail according to metrics

The rewriting phase will be responsible for modifying the message, obtained by the search phase, as necessary so that it has the style corresponding to the final recipient of the e-mail. To achieve this, we will need to know the category to which the person who will receive the message belongs. For this purpose, we will consult their e-mail address in the database where we can find the classification of the different contacts. In case no information is found about the consulted address, it will be necessary for the user to provide the category to which he or she belongs. As we will explain, this system requires to have previously data (written e-mails from which their style metrics have been extracted) of the category to which the recipient belongs, which can be a problem in case we consider writing a message destined to a new category.

As we have explained (see Chapter 5), there are eight style metrics of the initial twenty-eight that best describe the writing style depending on the recipient of the message. These style markers are: *verbAdjectiveRatio* (it is obtained by dividing the number of verbs by the number of adjectives), *detPronRatio* (it is obtained by dividing the number of determinants by the number of pronouns), *meanSentLen* (it is the average sentence length in word count), *meanWordLen* (it is the average word length in number of characters), *richnessYule* (it depends on the diversity of words, i.e. the number of different words and the number of words we do not repeat or appear twice, three, etc.), *difficultyLevel* (it depends on both the percentage of words with one or two characters and the *meanSentLen*), *stopRatio* (it is the percentage of stop words) and *entropy* (it depends on the number of times the same word appears). The modification of the e-mail will be based on trying to vary the value of these features according to the category to which the recipient belongs. In this way, we will obtain a message with values close to the averages of the style metrics of the category under consideration. There are several methods (with which we must assume that the message generated may not be correct due to issues such as polysemy and concordance in gender and number, among others) to modify them:

- Change the number of adjectives: removing adjectives is a simple task to perform and, except in cases where the adjective differentiates one entity from another, it does not cause problems when modifying the text. However, adding them is slightly more complicated. For this purpose, we could use a corpus of n-grams (like the Google n-grams[1]) to write the adjective that most commonly accompanies the noun at hand. Another way to address this problem is to add the adjectives according to the frequency with which the user uses them (using techniques such as probabilistic grammars used by Halliday (2014)) making use of the stored messages. The disadvantage of the latter method is that it requires a large number of e-mails and with one as small as ours, it is likely that good results would not be obtained. On the other hand, this solution guarantees the use of the user's *lexicon* (set of words used). The modification of the number of adjectives, will allow us to vary the following style metrics: *verAdjectiveRatio* (although changing the number of verbs can be a complex task and we can find many problems, as we have seen, changing the number of adjectives is feasible), *menaSentLen*, *difficultyLevel* (as it affects the average length of sentences), *richnessYule* (as it depends on the number of different words and the

[1] `http://storage.googleapis.com/books/ngrams/books/datasetsv2.html`

amount of times each word appears), *stopRatio* (as it adds or removes adjectives, the percentage of stop words will be modified) and *entropy* (changing the number of words in the text also changes the probability of each word appearing).

- Substitute words for synonyms: Although we may make mistakes in cases such as polysemic words, replacing words with their synonyms would allow us to increase or decrease the value of some style metrics. To obtain the corresponding synonyms there are many web services[2] or corpus from which we can extract them. Besides, we can use our bag of words (*wordsAppearance* style marker) in order to use synonyms which belong to the user's *lexicon*. The style metrics that would change their value with this method would be: *meanWordLen* (it is possible to replace some words with longer or shorter synonyms to modify this feature), *difficultyLevel* (as it also depends on the number of words in a syllable, although in our implementation it is the number of words with one or two characters, the replacement by synonyms of greater or lesser length can vary this descriptor), *richnessYule* and *entropy* (if a word is replaced by a synonym, its probability of occurrence decreases and that of the synonym used increases).

- Change the number of adverbs: the elimination of adverbs may not be as easy as in the case of adjectives, as these express circumstances, such as mode, place, time, quantity, affirmation, doubt, etc. Nevertheless, it is possible to add or remove adverbs of quantity or similar (such as very, little or quite). To carry out this task we can use the same methods we used with adjectives: corpus of n-grams or reusing the ones written by the user in the analysed e-mails. This modification of the text would affect the following metrics: *meanSentLen*, *difficultyLevel*, *richnessYule*, *stopRatio* and *entropy*.

- Change the number of pronouns: When trying to remove or add pronouns we will be faced with the problem of co-reference, which consists of knowing to which entity each of the pronouns in the text refer. Nowadays we find some models to solve this challenge with quite promising results. The solutions use all kinds of techniques, such as the neural net scoring model that spaCy has[3] (which is an implementation of the study of Clark and Manning (2016)). Replacing an entity with a pronoun (i.e. reducing the number of pronouns) is not a complicated task, it just requires taking into account parameters, such as gender or number, that are offered by syntactic analysers such as spaCy. On the other hand, the opposite task involves the co-reference problem mentioned. One possible solution is to use existing complex systems such as the one we have presented. Another possibility is to take advantage of the characteristics of e-mails to obtain co-reference results to text pronouns. As e-mails are not very complex texts and do not usually involve many entities, it is possible to obtain a large percentage of successes by looking for nouns that have the same number and gender and staying with the most numerous or the closest to the pronoun. In any case, the modification of the number of pronouns in the text would affect the following style metrics: *detPronRatio*, *meanSentLen*, *stopRatio*, *difficultyLevel*, *richnessYule* and *entropy*.

With these modifications of the original message, it will be possible to bring its style metrics closer to the desired value. However, it is necessary to underline that each one of

[2] such as `https://holstein.fdi.ucm.es/nil-ws-api/`
[3] `https://spacy.io/universe/project/neuralcoref`

these affects more than one style markers, which means that we are significantly varying the value of more than one metric. In the presentation of this model, we are assuming, as the logic indicates, that all these descriptors are slightly correlated, either in directly or inversely proportional way. Nevertheless, we run the risk of making use of one of the four previous changes and approaching the desired value of a feature while we are moving away from the mean of other style metric.

If we are able to change the values of the eight chosen style markers to its corresponding mean according to the category of the contact, we will have a text of the personalised message based on the recipient as we wanted to obtain.

Chapter 7

Conclusions and Future Work

"Difficult to see. Always in motion is the future."
— Yoda - Star Wars: Episode III – Revenge of the Sith (2005)

After the development of this work, in this chapter we present the conclusions that we can extract from our study. These are explained in Section 7.1. Then, the possible option for the continuation of this work are presented in Section 7.2 in order to follow with the research of the metrics that define the style based on the recipient of the message and take benefit of this field of study to build natural language generation systems that create e-mails.

7.1. Conclusions

Nowadays, electronic mail is a popular communication system both in professional scene and the personal one. Through it we establish conversations about work, studies and close relationships, among others. However, we do not express an idea to different people in the same way. Depends on our relationship we can vary our vocabulary, expressions, syntactic constructions or formality in our messages with the purpose of transmitting the same idea. In this work we were interested in this modification of the writing style of the same author when the recipient of the e-mail changes. In other words, we were curious to know the stylometric parameters which vary according to the addressee. If we could figure style metrics out, we would be able to personalise the automatic composition of messages of a natural language generation system.

In order to find out the metrics that defines the writing style according to the recipient of the message, it was necessary to obtain a sufficient amount of e-mails. Nevertheless, we have to not only extract them but measure them with a big set of style descriptors. For this reason, we developed a Style Analyser which carries out all the related tasks with the extraction and measurement of the messages of a given user. In particular, we have implemented the process of extracting the different e-mails of the user, preprocessing of the body of each message, correcting the possible typographic mistakes that can appear in the text and measuring the message written by the user.

For the extraction of the e-mails we had to learn about both the protocols and format of electronic mails. Moreover, as the messages that were going to be extracted specifically belonged to a Gmail account, we developed a module able to make use of the Gmail API for the accessing to the user's account information.

Preprocessing a message consists of modifying the e-mail body text with the purpose of

having the original message, without the headers and characters introduced by the e-mail service in order to follow the transmission protocol. With this in mind, a preprocessing module was developed as a web service, which allows it to work independently from the rest of the system and be easily reusable in other projects. This type of implementation is repeated in the typographic correction and style measuring modules, which needed to use a syntactic analyser for the successful of their tasks. Moreover, for the development of style measuring modules, it was necessary to learn about the different metrics used in the field of computational stylometry and implement them.

Once we had a functional style analyser, we measures the sent message of a user in order to obtain conclusions about the relationship between the implemented metrics and the style used for each recipient. In our data analysis, we concluded that, even though the chosen set of metrics do not differentiate the type of recipients well enough, there are features that describes the writing style better than others and we could select eight of them. We also observed that the obtained results were very dependent on the data, which means that we were limited by the not-so-large number of analysed messages and the unbalanced distribution of types of recipients that the e-mails had.

Many style metrics with more relevance (four out of eight) were related to the variety of different words used in the message. In other words, we are able to claim that the distribution of the vocabulary used, plays an important role in the description of writing style based on the recipient. The rest of them took into account features like the relationship between lexical categories (such as verbs and adjectives or determinants and pronouns) and the length of the sentences or words.

Finally, with this information we designed a model of message generation based on the recipient. The system's input is a set of keywords and the e-mail address which is going to receive the message. It makes use of the chosen metrics in order to modify the text until it presents the appropriate values for the recipient under consideration.

It is important to underline that we have not found any research about the writing style based on the recipient or audience of the message whether it is an e-mail or any written. Likewise, we are able to claim that this work is a first step in this research area and it lays the foundations for the natural language generation with style based on the person who is going to receive the information. In particular, it establishes the bases of the recipient-based personalised writing of e-mails.

7.2. Future Work

During the analysis of the data obtained after measuring the extracted e-mails, we found some obstacles against the attainment of significant results. One of the most relevant issues that we found is the amount of extracted messages. Since we have implemented most of the modules of the style analyser as web services, it could be easily adapted as a web service with the purpose of being accessible for a bigger amount of people and consequently being able to extract and measure a bigger number of e-mails. Perhaps, this adjustment could require to remove from the analysis process the typographic correction step, otherwise the users would have to correct their messages one by one.

Following with the possible improvements of the style analyser, we could consider (and implement) more style metrics in order to measure the different messages. As we have explained in Section 2.2.4, we can choose between at least a thousand stylistic features. From most simple descriptors, such as Burrow's Delta (Burrows, 2002), to the complex style markers, such as n-grams (Brocardo et al., 2013), and e-mail-specific features, such as the set of HTML tags (De Vel et al., 2001), we can enlarge our set of metrics. This

would allow us to test the variance of each new style descriptor between the different type of recipients.

Once we had measured a big amount of e-mails, we would be ready to carry out a data analysis with more relevant results. It would be appropriate to obtain a balance distribution of the different type of relationship with the recipients, thereby we would have different clusters with a similar number of samples which would allow us to use different machine learning techniques.

Taking advantage of conclusions obtained from this work, its natural extension is the implementation of the proposed model for generating personalised messages based on its recipient (see Chapter 6). As we can remember, it had two phases: searching phase and rewriting phase. The first of it is implemented in the Github repository, so it will only be necessary to develop the second module. In its implementation we will have to take into account the most representative metrics that describe the style depending on the recipient of the e-mail. This module could be used for any natural language generation system with the purpose of modifying the style of the generated text.

Bibliography

And thus I clothe my naked villany
With old odd ends stolen out of holy writ;
And seem a saint, when most I play the devil.

Richard III, Act I Scene 3
William Shakespeare

Abbasi, A. and Chen, H. Applying authorship analysis to extremist-group web forum messages. *IEEE Intelligent Systems*, Vol. 20(5), 67–75, 2005.

Abbasi, A. and Chen, H. Writeprints: A stylometric approach to identity-level identification and similarity detection in cyberspace. *ACM Transactions on Information Systems (TOIS)*, Vol. 26(2), 1–29, 2008.

Allen, J. R. Methods of author identification through stylistic analysis. *The French Review*, Vol. 47(5), 904–916, 1974.

Antosch, F. The diagnosis of literary style with the verb-adjective ratio. *Statistics and style*, Vol. 1, 1969.

Apte, C., Damerau, F., Weiss, S. et al. *Text mining with decision rules and decision trees*. Citeseer, 1998.

Argamon, S. Interpreting burrows's delta: Geometric and probabilistic foundations. *Literary and Linguistic Computing*, Vol. 23(2), 131–147, 2008.

Argamon, S., Koppel, M. and Avneri, G. Routing documents according to style. In *First International workshop on innovative information systems*, 85–92. 1998.

Argamon, S., Šarić, M. and Stein, S. S. Style mining of electronic messages for multiple authorship discrimination: first results. In *Proceedings of the ninth ACM SIGKDD international conference on Knowledge discovery and data mining*, 475–480. 2003.

Argamon-Engelson, S., Koppel, M. and Avneri, G. Style-based text categorization: What newspaper am i reading. In *Proc. of the AAAI Workshop on Text Categorization*, 1–4. 1998.

Baayen, H., van Halteren, H., Neijt, A. and Tweedie, F. An experiment in authorship attribution. In *6th JADT*, Vol. 1, 69–75. 2002.

Baayen, H., Van Halteren, H. and Tweedie, F. Outside the cave of shadows: Using syntactic annotation to enhance authorship attribution. *Literary and Linguistic Computing*, Vol. 11(3), 121–132, 1996.

Baayen, R., Tweedie, F., Neijt, A., Halteren, H. v. and Krebbers, L. Back to the cave of shadows: Stylistic fingerprints in authorship attribution. 2000.

Balenson, D. Privacy enhancement for internet electronic mail: Part iii: Algorithms, modes, and identifiers. Tech. Rep. RFC 1423, Internet Engineering Task Force (IETF), 1993.

Bartell, B. T., Cottrell, G. W. and Belew, R. K. Latent semantic indexing is an optimal special case of multidimensional scaling. In *Proceedings of the 15th annual international ACM SIGIR conference on Research and development in information retrieval*, 161–167. 1992.

BBC news (3rd July 2018). Gmail messages 'read by human third parties'. *Technology*, 2018. `https://www.bbc.com/news/technology-44699263`.

Benesty, J., Chen, J., Huang, Y. and Cohen, I. Pearson correlation coefficient. In *Noise reduction in speech processing*, 1–4. Springer, 2009.

Binongo, J. N. G. and Smith, M. W. A. The application of principal component analysis to stylometry. *Literary and Linguistic Computing*, Vol. 14(4), 445–466, 1999.

Borenstein, N. and Freed, N. Mime (multipurpose internet mail extensions) part one: Mechanisms for specifying and describing the format of internet message bodies. Tech. Rep. RFC 1521, Internet Engineering Task Force (IETF), 1993.

Brainerd, B. *Weighting Evidence in Language and Literature: A Statistical Approach*. University of Toronto Press, 1974.

Breiman, L. Random forests. *Machine learning*, Vol. 45(1), 5–32, 2001.

Breiman, L., Friedman, J., Stone, C. J. and Olshen, R. A. *Classification and regression trees*. CRC press, 1984.

Brocardo, M. L., Traore, I., Saad, S. and Woungang, I. Authorship verification for short messages using stylometry. In *2013 International Conference on Computer, Information and Telecommunication Systems (CITS)*, 1–6. IEEE, 2013.

Burrows, J. 'delta': a measure of stylistic difference and a guide to likely authorship. *Literary and linguistic computing*, Vol. 17(3), 267–287, 2002.

Burrows, J. F. Computers and the study of literature. *Computers and written texts*, 167–204, 1992.

Calix, K., Connors, M., Levy, D., Manzar, H., MCabe, G. and Westcott, S. Stylometry for e-mail author identification and authentication. *Proceedings of CSIS research day, Pace University*, 1048–1054, 2008.

Canales, O., Monaco, V., Murphy, T., Zych, E., Stewart, J., Castro, C. T. A., Sotoye, O., Torres, L. and Truley, G. A stylometry system for authenticating students taking online tests. *P. of Student-Faculty Research Day, Ed., CSIS. Pace University*, 2011.

Casey, M., Rhodes, C. and Slaney, M. Analysis of minimum distances in high-dimensional musical spaces. *IEEE Transactions on Audio, Speech, and Language Processing*, Vol. 16(5), 1015–1028, 2008.

Chaski, C. E. Empirical evaluations of language-based author identification techniques. *Forensic Linguistics*, Vol. 8, 1–65, 2001.

Chen, X., Hao, P., Chandramouli, R. and Subbalakshmi, K. Authorship similarity detection from email messages. In *International Workshop on Machine Learning and Data Mining in Pattern Recognition*, 375–386. Springer, 2011.

Cheng, N., Chandramouli, R. and Subbalakshmi, K. Author gender identification from text. *Digital Investigation*, Vol. 8(1), 78–88, 2011.

Chi, J. T., Chi, E. C. and Baraniuk, R. G. k-pod: A method for k-means clustering of missing data. *The American Statistician*, Vol. 70(1), 91–99, 2016.

Cho, J. H. and Kurup, P. U. Decision tree approach for classification and dimensionality reduction of electronic nose data. *Sensors and Actuators B: Chemical*, Vol. 160(1), 542–548, 2011.

Choi, J. D., Tetreault, J. and Stent, A. It depends: Dependency parser comparison using a web-based evaluation tool. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, 387–396. 2015.

Chowdhury, G. G. *Introduction to modern information retrieval*. Facet publishing, 2010.

Clark, K. and Manning, C. D. Deep reinforcement learning for mention-ranking coreference models. *arXiv preprint arXiv:1609.08667*, 2016.

Cohen, W. W. et al. Learning rules that classify e-mail. In *AAAI spring symposium on machine learning in information access*, Vol. 18, 25. Stanford, CA, 1996.

Cook, B. and Messina, C. OAuth 2.0. `https://oauth.net/2/`, 2019a. [Online; accessed 27-September-2019].

Cook, B. and Messina, C. OAuth 2.0 Authorization Code Exchange. `https://www.oauth.com/oauth2-servers/pkce/authorization-code-exchange/`, 2019b. [Online; accessed 27-September-2019].

Cook, B. and Messina, C. OAuth 2.0 Scope. `https://oauth.net/2/scope/`, 2019c. [Online; accessed 27-September-2019].

Corney, M. W. *Analysing e-mail text authorship for forensic purposes*. PhD thesis, Queensland University of Technology, 2003.

Corney, M. W., Anderson, A. M., Mohay, G. M. and de Vel, O. Identifying the authors of suspect email. 2001.

Craig, H. Authorial attribution and computational stylistics: If you can tell authors apart, have you learned anything about them? *Literary and Linguistic Computing*, Vol. 14(1), 103–113, 1999.

Crispin, M. Internet message access protocol - version 4rev1. Tech. Rep. RFC 3501, University of Washington, 2003.

Crocker, D. H. Standard for the format of arpa internet text messages. Tech. Rep. RFC 822, Dept. of Electrical Engineering, University of Delaware, 1982.

Daelemans, W., De Clercq, O. and Hoste, V. STYLENE: an environment for stylometry and readability research for Dutch. In *CLARIN in the Low Countries*, 195–210. Ubiquity Press, 2017.

Dale, E. and Chall, J. S. A formula for predicting readability: Instructions. *Educational research bulletin*, 37–54, 1948.

De Morgan, S. E. and De Morgan, A. *Memoir of Augustus De Morgan*. Longmans, Green, and Company, 1882.

De Vel, O., Anderson, A., Corney, M. and Mohay, G. Mining e-mail content for author identification forensics. *ACM Sigmod Record*, Vol. 30(4), 55–64, 2001.

Deerwester, S., Dumais, S. T., Furnas, G. W., Landauer, T. K. and Harshman, R. Indexing by latent semantic analysis. *Journal of the American society for information science*, Vol. 41(6), 391–407, 1990.

Diederich, J., Kindermann, J., Leopold, E. and Paass, G. Authorship attribution with support vector machines. *Applied intelligence*, Vol. 19(1-2), 109–123, 2003.

Ding, C. H. A similarity-based probability model for latent semantic indexing. In *Proceedings of the 22nd annual international ACM SIGIR conference on Research and development in information retrieval*, 58–65. 1999.

Drucker, H., Wu, D. and Vapnik, V. N. Support vector machines for spam categorization. *IEEE Transactions on Neural networks*, Vol. 10(5), 1048–1054, 1999.

DuBay, W. H. The principles of readability. *Online Submission*, 2004.

Dumais, S. T. et al. Latent semantic indexing (lsi): Trec-3 report. *Nist Special Publication SP*, 219–219, 1995.

Eder, M. Style-markers in authorship attribution: a cross-language study of the authorial fingerprint. *Studies in Polish Linguistics*, Vol. 6(1), 2011.

Eder, M., Rybicki, J. and Kestemont, M. Stylometry with r: a package for computational text analysis. *R journal*, Vol. 8(1), 2016.

Ellegard, A. A statistical method for determining authorship: the junius letter. *Gothenburg studies in Engilsh*, Vol. 13, 1769–1772, 1962.

Ester, M., Kriegel, H.-P., Sander, J., Xu, X. et al. A density-based algorithm for discovering clusters in large spatial databases with noise. In *Kdd*, Vol. 96, 226–231. 1996.

Feng, S., Banerjee, R. and Choi, Y. Syntactic stylometry for deception detection. In *Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics: Short Papers-Volume 2*, 171–175. Association for Computational Linguistics, 2012.

Freed, N. and Borenstein, N. Mime (multipurpose internet mail extensions). Tech. Rep. RFC 1341, Internet Engineering Task Force (IETF), 1992.

Freed, N. and Borenstein, N. Multipurpose internet mail extensions (mime) part five: Conformance criteria and examples. Tech. Rep. RFC 2049, Internet Engineering Task Force (IETF), 1996a.

Freed, N. and Borenstein, N. Multipurpose internet mail extensions (mime) part one: Format of internet message bodies. Tech. Rep. RFC 2045, Internet Engineering Task Force (IETF), 1996b.

Freed, N. and Borenstein, N. Multipurpose internet mail extensions (mime) part two: Media types. Tech. Rep. RFC 2046, Internet Engineering Task Force (IETF), 1996c.

Freed, N. and Klensin, J. Media type specifications and registration procedures. Tech. Rep. RFC 4288, Internet Engineering Task Force (IETF), 2005a.

Freed, N. and Klensin, J. Multipurpose internet mail extensions (mime) part four: Registration procedures. Tech. Rep. RFC 4289, Internet Engineering Task Force (IETF), 2005b.

Fucks, W. and Lauter, J. Mathematische analyse des literarischen stils.–mathematik und dichtung. versuche zur frage einer exakten literaturwissenschaft. 1965.

Gatt, A. and Krahmer, E. Survey of the state of the art in natural language generation: Core tasks, applications and evaluation. *Journal of Artificial Intelligence Research*, Vol. 61, 65–170, 2018.

Gellens, R. The text/plain format parameter. Tech. Rep. RFC 2646, Internet Engineering Task Force (IETF), 1999.

Golub, G. H. and Reinsch, C. Singular value decomposition and least squares solutions. In *Linear Algebra*, 134–151. Springer, 1971.

Google. Gmail api | google developers. `https://developers.google.com/gmail/api`, 2019a. [Online; accessed 17-October-2019].

Google. google_auth_oauthlib.flow module. `https://google-auth-oauthlib.readthedocs.io/en/latest/reference/google_auth_oauthlib.flow.html`, 2019b. [Online; accessed 27-September-2019].

Google. google.auth.transport package. `https://google-auth.readthedocs.io/en/stable/reference/google.auth.transport.html#google.auth.transport.Request`, 2019c. [Online; accessed 27-September-2019].

Google. google.oauth2.credentials module. `https://google-auth.readthedocs.io/en/stable/reference/google.oauth2.credentials.html#google.oauth2.credentials.Credentials`, 2019d. [Online; accessed 27-September-2019].

Google. OAuth 2.0 Scopes for Google APIs. `https://developers.google.com/identity/protocols/googlescopes`, 2019e. [Online; accessed 27-September-2019].

Google. Using OAuth 2.0 to Access Google APIs. `https://developers.google.com/identity/protocols/OAuth`, 2019f. [Online; accessed 27-September-2019].

Gregorio, J. googleapiclient.discovery. `https://googleapis.github.io/google-api-python-client/docs/epy/googleapiclient.discovery-module.html#build`, 2019. [Online; accessed 23-September-2019].

Gruner, S. and Naven, S. Tool support for plagiarism detection in text documents. In *Proceedings of the 2005 ACM symposium on Applied computing*, 776–781. 2005.

Guide, S. *Red Hat Enterprise Linux 4: Reference Guide*. Red Hat Inc., 2005. `http://web.mit.edu/rhel-doc/OldFiles/4/RH-DOCS/rhel-rg-en-4/index.html`.

Gunning, R. The technique of clear writing. *Revised Edition. New York: McGraw Hill*, 1968.

Győrödi, C., Győrödi, R., Pecherle, G. and Olah, A. A comparative study: Mongodb vs. mysql. In *2015 13th International Conference on Engineering of Modern Electric Systems (EMES)*, 1–6. IEEE, 2015.

Halliday, M. A. Corpus studies and probabilistic grammar. In *English corpus linguistics*, 42–55. Routledge, 2014.

Hardt, D. The oauth 2.0 authorization framework. Tech. Rep. RFC 6749, Internet Engineering Task Force (IETF), 2012.

Hartigan, J. A. *Clustering algorithms*. John Wiley & Sons, Inc., 1975.

Hofmann, T. Probabilistic latent semantic indexing. In *Proceedings of the 22nd annual international ACM SIGIR conference on Research and development in information retrieval*, 50–57. 1999.

Holmes, D. I. The analysis of literary style—a review. *Journal of the Royal Statistical Society: Series A (General)*, Vol. 148(4), 328–341, 1985.

Holmes, D. I. The evolution of stylometry in humanities scholarship. *Literary and linguistic computing*, Vol. 13(3), 111–117, 1998.

Holmes, D. I. and Forsyth, R. S. The federalist revisited: New directions in authorship attribution. *Literary and Linguistic computing*, Vol. 10(2), 111–127, 1995.

Homem, N. and Carvalho, J. P. Authorship identification and author fuzzy "fingerprints". In *2011 Annual Meeting of the North American Fuzzy Information Processing Society*, 1–6. IEEE, 2011.

Honnibal, M. and Johnson, M. An improved non-monotonic transition system for dependency parsing. In *Proceedings of the 2015 conference on empirical methods in natural language processing*, 1373–1378. 2015.

Honoré, A. Some simple measures of richness of vocabulary. *Association for literary and linguistic computing bulletin*, Vol. 7(2), 172–177, 1979.

Hoover, D. L. Delta prime? *Literary and Linguistic Computing*, Vol. 19(4), 477–495, 2004a.

Hoover, D. L. Testing burrows's delta. *Literary and linguistic computing*, Vol. 19(4), 453–475, 2004b.

Hughes, J. M., Foti, N. J., Krakauer, D. C. and Rockmore, D. N. Quantitative patterns of stylistic influence in the evolution of literature. *Proceedings of the National Academy of Sciences*, Vol. 109(20), 7682–7686, 2012.

Hughes, J. M., Graham, D. J. and Rockmore, D. N. Quantification of artistic style through sparse coding analysis in the drawings of pieter bruegel the elder. *Proceedings of the National Academy of Sciences*, Vol. 107(4), 1279–1283, 2010.

Huron, D. The ramp archetype: A score-based study of musical dynamics in 14 piano composers. *Psychology of Music*, Vol. 19(1), 33–45, 1991.

Ibrahim, M. S., Kasim, S., Hassan, R., Mahdin, H., Ramli, A. A., Fudzee, M. F. M., Salamat, M. A. et al. Information technology club management system. *Acta Electronica Malaysia*, Vol. 2(2), 01–05, 2018.

Iqbal, F., Binsalleeh, H., Fung, B. C. and Debbabi, M. Mining writeprints from anonymous e-mails for forensic investigation. *digital investigation*, Vol. 7(1-2), 56–64, 2010.

Jones, K. S. A statistical interpretation of term specificity and its application in retrieval. *Journal of documentation*, 1972.

Josefsson, S. The base16, base32, and base64 data encodings. Tech. Rep. RFC 4648, Internet Engineering Task Force (IETF), 2006.

Juola, P. Becoming jack london. *Journal of Quantitative Linguistics*, Vol. 14(2-3), 145–147, 2007.

Kaliski, B. Privacy enhancement for internet electronic mail: Part iv: Key certification and related services. Tech. Rep. RFC 1424, Internet Engineering Task Force (IETF), 1993.

Kemp, K. W. Personal observations on the use of statistical methods in quantitative linguistics. In *The Computer in Literary and Linguistic Studies (Proceeding, Third International Symposium)*, 59–77. 1976.

Kent, S. Privacy enhancement for internet electronic mail: Part ii: Certificate-based key management. Tech. Rep. RFC 1422, Internet Engineering Task Force (IETF), 1993.

Kjell, B., Woods, W. A. and Frieder, O. Discrimination of authorship using visualization. *Information processing & management*, Vol. 30(1), 141–150, 1994.

Kjetsaa, G. And quiet flows the don through the computer. *Association for Literary and linguistic computing Bulletin*, Vol. 7, 248–256, 1979.

Klensin, J. Simple mail transfer protocol. Tech. Rep. RFC 5321, Internet Engineering Task Force (IETF), 2008.

Koppel, M., Akiva, N. and Dagan, I. Feature instability as a criterion for selecting potential style markers. *Journal of the American Society for Information Science and Technology*, Vol. 57(11), 1519–1525, 2006.

Koppel, M. and Schler, J. Exploiting stylistic idiosyncrasies for authorship attribution. In *Proceedings of IJCAI'03 Workshop on Computational Approaches to Style Analysis and Synthesis*, Vol. 69, 72–80. 2003.

Kucukyilmaz, T., Cambazoglu, B. B., Aykanat, C. and Can, F. Chat mining: Predicting user and message attributes in computer-mediated communication. *Information Processing & Management*, Vol. 44(4), 1448–1466, 2008.

Landauer, T. K., Laham, D. and Foltz, P. W. Learning human-like knowledge by singular value decomposition: A progress report. In *Advances in neural information processing systems*, 45–51. 1998.

Linn, J. Privacy enhancement for internet electronic mail: Part i: Message encryption and authentication procedures. Tech. Rep. RFC 1421, Internet Engineering Task Force (IETF), 1993.

Manaris, B., Romero, J., Machado, P., Krehbiel, D., Hirzel, T., Pharr, W. and Davis, R. B. Zipf's law, music classification, and aesthetics. *Computer Music Journal*, Vol. 29(1), 55–69, 2005.

Mendenhall, T. C. The characteristic curves of composition. *Science*, Vol. 9(214), 237–249, 1887.

Mihalcea, R. and Strapparava, C. The lie detector: Explorations in the automatic recognition of deceptive language. In *Proceedings of the ACL-IJCNLP 2009 Conference Short Papers*, 309–312. Association for Computational Linguistics, 2009.

Moore, K. Multipurpose internet mail extensions (mime) part three: Message header extensions for non-ascii text. Tech. Rep. RFC 2047, Internet Engineering Task Force (IETF), 1996.

Mosteller, F. and Wallace, D. L. *Applied Bayesian and classical inference: the case of the Federalist papers*. Springer Science & Business Media, 1964.

Myers, J., Mellon, C. and Rose, M. Post office protocol - version 3. Tech. Rep. RFC 1939, Dover Beach Consulting, Inc., 1996.

Nelson, S. and Parks, C. The model primary content type for multipurpose internet mail extensions. Tech. Rep. RFC 2077, Internet Engineering Task Force (IETF), 1997.

Ng, H. T., Goh, W. B. and Low, K. L. Feature selection, perceptron learning, and a usability case study for text categorization. In *Proceedings of the 20th annual international ACM SIGIR conference on Research and development in information retrieval*, 67–73. 1997.

Nielsen, F. Hierarchical clustering. In *Introduction to HPC with MPI for Data Science*, 195–211. Springer, 2016.

Ott, M., Choi, Y., Cardie, C. and Hancock, J. T. Finding deceptive opinion spam by any stretch of the imagination. In *Proceedings of the 49th annual meeting of the association for computational linguistics: Human language technologies-volume 1*, 309–319. Association for Computational Linguistics, 2011.

Pennebaker, J. W., Boyd, R. L., Jordan, K. and Blackburn, K. The development and psychometric properties of liwc2015. Tech. rep., University of Texas at Austin, 2015.

Postel, J. B. Simple mail transfer protocol. Tech. Rep. RFC 821, Information Sciences Institute, University of Southern California, 1982.

Rand, W. M. Objective criteria for the evaluation of clustering methods. *Journal of the American Statistical association*, Vol. 66(336), 846–850, 1971.

Reiter, E. and Dale, R. *Building natural language generation systems*. Cambridge university press, 2000.

Resnick, P. Internet message format. Tech. Rep. RFC 2822, Internet Engineering Task Force (IETF), 2001.

Resnick, P. Internet message format. Tech. Rep. RFC 5322, Qualcomm Incorporated, 2008.

Reynolds, J. K. Post office protocol. Tech. Rep. RFC 918, Information Sciences Institute, 1984.

Ril Gil, Y., Toll Palma, Y. d. C. and Lahens, E. F. Determination of writing styles to detect similarities in digital documents. *RUSC: Revista de Universidad y Sociedad del Conocimiento*, Vol. 11(1), 2014.

Rokach, L. and Maimon, O. Z. *Data mining with decision trees: theory and applications*, Vol. 69. World scientific, 2008.

Rousseeuw, P. J. Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. *Journal of computational and applied mathematics*, Vol. 20, 53–65, 1987.

Rudman, J. The state of authorship attribution studies: Some problems and solutions. *Computers and the Humanities*, Vol. 31(4), 351–365, 1997.

Sahami, M., Dumais, S., Heckerman, D. and Horvitz, E. A bayesian approach to filtering junk e-mail. In *Learning for Text Categorization: Papers from the 1998 workshop*, Vol. 62, 98–105. Madison, Wisconsin, 1998.

Sapp, C. Hybrid numeric/rank similarity metrics for musical performance analysis. In *ISMIR*, 501–506. Citeseer, 2008.

Sasaki, M. and Shinnou, H. Spam detection using text clustering. In *2005 International Conference on Cyberworlds (CW'05)*, 4–pp. IEEE, 2005.

Schwartz, H. A., Eichstaedt, J. C., Kern, M. L., Dziurzynski, L., Ramones, S. M., Agrawal, M., Shah, A., Kosinski, M., Stillwell, D., Seligman, M. E. et al. Personality, gender, and age in the language of social media: The open-vocabulary approach. *PloS one*, Vol. 8(9), e73791, 2013.

Segal, R. B. and Kephart, J. O. Mailcat: An intelligent assistant for organizing e-mail. In *Proceedings of the third annual conference on Autonomous Agents*, 276–282. 1999.

Sheika, F. A. and Inkpen, D. Learning to classify documents according to formal and informal style. *Linguistic Issues in Language Technology*, Vol. 8(1), 1–29, 2012.

Simpson, E. H. Measurement of diversity. *nature*, Vol. 163(4148), 688–688, 1949.

Smith, M. W. Recent experience and new developments of methods for the determination of authorship. *ALLC BULL.*, Vol. 11(3), 73–82, 1983.

Somers, H. Statistical methods in literary analysis. *The computer and literary style*, 128–140, 1966.

Stamatatos, E. A survey of modern authorship attribution methods. *Journal of the American Society for information Science and Technology*, Vol. 60(3), 538–556, 2009.

Stamou, C. Stylochronometry: Stylistic development, sequence of composition, and relative dating. *Literary and Linguistic Computing*, Vol. 23(2), 181–199, 2007.

Stewart, G. W. On the early history of the singular value decomposition. *SIAM review*, Vol. 35(4), 551–566, 1993.

Sugumaran, V., Muralidharan, V. and Ramachandran, K. Feature selection using decision tree and classification through proximal support vector machine for fault diagnostics of roller bearing. *Mechanical systems and signal processing*, Vol. 21(2), 930–942, 2007.

Summers, K. Analysing for authorship: A guide to the cusum technique. 1999.

Tallentire, D. *An appraisal of methods and models in computational stylistics, with particular reference to author attribution.*. PhD thesis, University of Cambridge, 1972.

Tang, G., Pei, J. and Luk, W.-S. Email mining: tasks, common techniques, and tools. *Knowledge and Information Systems*, Vol. 41(1), 1–31, 2014.

Taylor, R. P., Micolich, A. P. and Jonas, D. Fractal analysis of pollock's drip paintings. *Nature*, Vol. 399(6735), 422–422, 1999.

Thisted, R. and Efron, B. Did shakespeare write a newly-discovered poem? *Biometrika*, Vol. 74(3), 445–455, 1987.

Thomson, R. and Murachver, T. Predicting gender from electronic discourse. *British Journal of Social Psychology*, Vol. 40(2), 193–208, 2001.

Troost, R., Dorner, S. and Moore, K. Communicating presentation information in internet messages: The content-disposition header field. Tech. Rep. RFC 2183, Internet Engineering Task Force (IETF), 1997.

Tweedie, F. J. and Baayen, R. H. How variable may a constant be? measures of lexical richness in perspective. *Computers and the Humanities*, Vol. 32(5), 323–352, 1998.

Tweedie, F. J., Singh, S. and Holmes, D. I. Neural network applications in stylometry: The federalist papers. *Computers and the Humanities*, Vol. 30(1), 1–10, 1996.

Williams, C. B. *Style and vocabulary: numerical studies*. Griffin, 1970.

Yule, C. U. *The statistical study of literary vocabulary*. Cambridge University Press, 2014.

Yule, G. U. On sentence-length as a statistical characteristic of style in prose: With application to two cases of disputed authorship. *Biometrika*, Vol. 30(3/4), 363–390, 1939.

Zhao, Y. and Zobel, J. Searching with style: Authorship attribution in classic literature. In *Proceedings of the thirtieth Australasian conference on Computer science-Volume 62*, 59–68. Australian Computer Society, Inc., 2007.