From T'es Qui to Qui Es-Tu:

A Naïve Bayesian Approach to Assessing Literate and Oral Discourse in Non-standard French Language Data

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Abstract

An overlooked aspect of communication is the conceptual, where literacy corresponds conceptually to written language, and orality corresponds conceptually to spoken language. Non-standard French language data was obtained from eBay, SMS chats and Wikiconflits to explore how these two facets are realized in different internet domains. Training data was automatically developed using classification criteria that is typical of literacy and orality in French. This data was then used to train a naïve Bayes model to assign the most probable conceptual classification feature to a document. The results show that those who use the platform eBay tend to express themselves conceptually in a more literate fashion. SMS chats display a high level of conceptual orality and Wikiconflits show a tendency be conversative in their orality.

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List of Abbreviations:

From T'es Qui to Qui Es-Tu

CMRW CMR-wikiconflits

CoMeRe Corpora of Computer-Mediated

Communication in French

EPA eBay petites annonces

FΑ français argotique

FCO Français courant

FCU Français cultivé

FRÉ Français écrit

FF Français familier

FPA Français parlé

FΡ Français populaire

FV Français vulgaire

LP Langue parlé

LT Langues techniques

MLE Maximum Likelihood Expectation

ΝZ Niveau zéro

NLP **Natural Language Processing**

OOV Out-of-Vocabulary

POS-Tagging Part of Speech Tagging

1. Introduction

Excluding other modes by which human communication can be realized such as via sign language, body language, whistling, etc., human languages are generally expressed medially through either text or speech (Bader, 2002). Oral, i.e., spoken discourse, can be understood as a process which employs audible sounds to express meaning, whereas literate, i.e., written discourse, is the visual medium that uses written symbols (Bader, 2002). An aspect that is often overlooked is conceptual discourse. In other words, what is the actual conceptual intent that a speaker wishes to communicate with their message? Does the speaker intend for their message to be more in line with spoken or written language?

With these distinctions in mind, the concepts of written vs. spoken and literacy vs. orality arise. The former represents the medial aspect of language, whereas the latter represents the conceptual intent of a speaker. These two domains do not represent a natural dichotomy, as one might automatically assume, but rather, they are two sectors of language that regularly overlap (Koch & Oesterreicher, 1985).

Determining the conceptual intent of a speaker's discourse is to be done using a multinomial naïve Bayes algorithm (Jurafsky & Martin, 2020). A simple, but effective smoothing algorithm as proposed by Ng (1997) will be used to solve the out-of-vocabulary problem. Multinomial naïve Bayes, which will be referred henceforth as naïve Bayes, requires training data for it to be able to properly determine the conceptual discourse type of a given document. Therefore, a classification system must first be developed that can automatically label documents according to their conceptual discourse type. This serves as the basis from which the naïve Bayes algorithm draws its training data and computes the discourse classification probabilities.

To explore the conceptual discourse in a more practical sense, French language data was chosen from three main internet domains: eBay, SMS and Wikiconflits. SMS chats were chosen as they are the most likely candidate for representing orality (Bader, 2002; Rehm 2002). These are then to contrast with the Wikiconflits chats, as the content therein pertains to scientific and intellectual communication, and therefore represents literacy (Koch & Oesterreicher, 1985). eBay postings are to be seen here as a control as they do not intrinsically represent one conceptual discourse style over another.

2. Related Works

2.1. Theoretical Linguistics

Koch and Oesterreicher (1985) constructed the medial-conceptual paradigm of written vs. spoken and literacy vs. orality by providing a situational context in which these two facets of language can occur. Koch and Oesterreicher (1985) also place focus on sociolinguistic contexts regarding this paradigm by expounding upon the notions of *Distanzsprache* and *Nähesprache*, which are additional factors crucial to identifying the correct discourse type. Koch and Oesterreicher (2007) offered a more detailed explanation regarding the medial and conceptual discourse types by expanding their examples and explanations to include German and English.

Even though Müller (1975) predates Koch and Oesterreicher (1985), the notion of literacy and orality was already known to Müller (1975) who refers to them as *français* parlé, message oral, languée and français écrit, message écrit, langue écrite, languge écrit respectively. Müller (1975) explores this distinction and how it is realized chronologically, quantitatively, qualitatively, diatopically, and diastratically within the French language.

2.2. Computational Linguistics

Ortmann and Dipper (2019) explore the ideas as proposed by various authors (Bader, 2002; Koch & Oesterreicher, 1985; Rehm, 2002) to be able to automatically identify literate and oral discourse in modern German texts. Ortmann and Dipper (2020) applied the same methodology to assess the literacy and orality regarding historical texts. Ortmann and Dipper (2020) did this by using a slightly altered feature set that is more fitting for historical texts, as the non-standardized nature of historical documents cannot be properly analyzed using modern criteria (Ortmann & Dipper, 2020).

Bader (2002) provides a rounded, general approach to properly assess literacy and orality in texts in the same vein as Müller (1975). However, Bader (2002) applies the analysis to digital communication, e.g., e-mail, chat, newsgroups, forums, while also providing features to identify the precise nature of individual excerpts from said communication. Rehm (2002) offers a more restricted analysis by only detailing the nature, characteristics and features of conceptual orality in written language on the internet e.g., e-mail, chat data, websites, etc. at the time of publication.

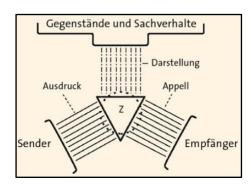
3. Language as a Construct

3.1. General Features of Language

Language, as a mode of communication, is something of which humans have been capable for around 100,000 years (Stein, 2014). Human language is first and foremost, the production of audible sounds, i.e., speech (Bader, 2002). Furthermore, language is the aggregation of conventions, norms, value and opposition. The value of a given word, be it phonetic or graphic, is that it can be distinguished from another element (Stein, 2014). If there is a distinction between these two elements, then opposition is present (Stein, 2014). Should they have the same function, then it would be necessary to refer to them as variants of one another (Stein, 2014). This leads into the distinction of langue versus parole, langue being the virtual construct of a given language that could be realized by a speaker and parole being the actual realization of langue (Stein, 2014).

Independent of the medial and conceptual of the language is how exactly communication can work between speakers. The organon model, as seen in figure 1, models the way in which linguistic information is received and processed. Every communication process consists of the following: sender, empfänger and gegenstände

und sachverhalte. Sender is the speaker, with empfänger being the listener. Gegenstände und sachverhalte are the messages being transmitted. All three of these are connected through Z which represents the language i.e., sprachliches zeichen (Stein, 2014). The sprachliches zeichen is what is transmitted via language. It has three main Figure 1. Bühler Organon-Modell functions: Ausdruck, darstellung, and appel. The



(Stein, 2014, p. 1)

ausdruck expresses the opinions and feelings of the speaker, which are the symptoms of the sprachliches zeichen (Stein, 2014). The darstellung is the symbol for the information while the appel elicits a desired response from the listener that is in line with the sprachliches Zeichen (Stein, 2014). All three are present in every message, but generally one will dominate over the others (Bader, 2002).

3.2. Medial Features

Spoken language in the can be understood as the phonetic expression of thought (Bader, 2002). This is in line with structural linguists, saw spoken language superseding and being the precursor of written language (Stein, 2014). Due to the nature of spoken language being the primary factor chronologically speaking (Bader, 2002; Koch and Oesterreicher, 1985), it is the medium that is the most prominent and the one that has been object of great discussion, especially since the 20th century (Bader, 2002; Stein, 2014).

Spoken language is a spontaneous act that is directly coupled with transience (Bader, 2002). This real-time process prevents spoken language from becoming overly complex as it would overload the listener's ability to ascertain the meaning from the message (Ortmann & Dipper, 2019).

The speaker's ability to be able to process the linguistic information in real-time also has a direct impact on syntax. Meaning that the active voice and elliptical structures are preferable in spoken language as they are easier to process (Ortmann & Dipper, 2019). This is evident in the lexical as spoken language makes frequent use of various particles, e.g., answer and modal particles, vague expressions, and interjections (Ortmann & Dipper, 2019)

If spoken language is the phonetic expression of thought, written language is then to be seen as a graphical depiction and recording of said thought (Bader, 2002; Stein, 2014). The reason as to why written language exists at all is explained by the fact that it is essential in transcribing thoughts and transporting messages over long temporal and physical distances (Bader, 2002).

Written language often contrasts with spoken language due the dichotomous nature of the language paradigm (Bader, 2002; Koch & Oesterreicher, 1985). Where spoken language is restricted to being less complex, written language can benefit from static properties of a textual medium (Ortmann & Dipper, 2019). This naturally carries over into the syntactical and lexical structure of any given written message. Syntactical and lexical properties can be expounded upon in general without having to take the speaker's ability to process information into consideration (Ortmann & Dipper, 2019).

It would be false to assume that spoken language can only represent spoken language and written language can only represent written language. An important property is that an author of written language can express orality through the omission of characters, i.e., missing spellings, word contractions, or use of ellipsis dots, em dashes or apostrophes (Ortmann & Dipper, 2019). The opposite is also true in that written language can also express literacy by strictly adhering to orthographic norms, employing complex syntactical structures and using lexically complex constructions (Bader, 2002; Ortmann & Dipper, 2019; Ortmann & Dipper, 2020).

3.3. Conceptual Features

Although it would be possible to see a dichotomy being present between literacy and orality, this is not strictly correct. The dichotomy does exist, but it only applies to the medial vs. conceptual. Regarding the medial representation, i.e., the graphic code and the phonetic code, a dichotomy is present. The other question remains though: What is to be done with the conceptual aspect of language? As the medial features of language directly contrast with those of conceptual, they can be grouped together as seen in figure 2.

	Konzeption		
		Gesprochen	Geschrieben
Madium	Graphischer Kode	Faut pas le dire	Il ne faut pas le dire
Medium	Phonischer Kode	[fopaldir]	[ilnəfplalədiʀ]

Figure 2. *Medium and Concept* (Koch & Oesterreicher, 1985, p. 17)

The medium is either the *phonischer kode*, i.e., spoken or it is the *graphischer kode*, i.e., written. This means that a message like *faut pas le dire* is medially representative of written language but is conceptually spoken language. It is conceptually representative of orality In this particular example due to the omission of il and ne, which are standard French (Koch & Oesterreicher, 1985; Müller, 1975). The opposite of this applies as well where *il ne faut pas le dire* is representative of literacy and written language as it complies with the written norms set forth by the governing linguistic bodies of the French language (Müller, 1975).

The phonetic element plays an important role as well but is only relevant if the message is audible. As text is not a medium that can transport audio, the phonetic

element does not necessarily apply here. It only applies indirectly if the speaker first starts with a phonetic message that is then transcribed graphically (Bader, 2002; Koch & Oesterreicher, 1985). Koch and Oesterreicher (1985) see spoken and written language

as being on a continuum with conceptual possibilities that have different levels which are exemplified in figure 3.

On the

phonisch ,i.e., phonic portion of

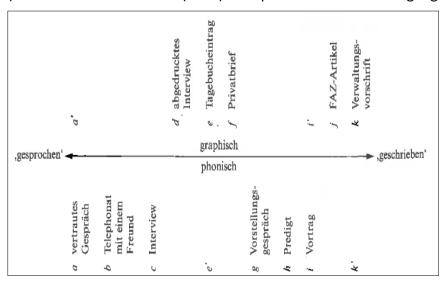


Figure 3. Spoken and Written vs. Graphic and Phonic (Koch & Oesterreicher, 1985, p. 18)

figure 3, all the texts are medially spoken, but conceptually start off as being representative of orality and gradually transition into literacy. The results in the language in the following texts become more representative conceptually of written discourse. When observing the two poles, there is a difference between a *vertrautes gespräch*, i.e., intimate conversation and a *vortrag*, i.e., presentation. The former represents spontaneous speech, with the latter being prefabricated and then presented to an audience orally (Koch & Oesterreicher, 1985).

On the *graphisch*, i.e., graphic portion of the diagram, all documents represent possible graphic representations of speech, with d, an *abgedrucktes Intervew*, i.e., prepared interview, being medially the most oral with, k, *verwaltungsvorschift*,i.e., an administrative regulation, being highly representative of literacy, while still being a medially oral.

Figure 3 demonstrates, what was tabularly presented in figure 2, which is that medial and conceptual discourse exist on a spectrum. An important element missing from figure 2 is how this relates to communication and discourse as was touched upon in figure 1. Figure 4 solves this dilemma, by presenting a dynamic, but combining figure 2 and 3 together.

Figure 4 address how close in terms of proximity and familiarity the speakers are to one another. Nähesprache or Sprache der Nähe, is reserved for situations that are physical and familiar in nature (Koch & Oesterreicher, 1985). This includes, but is not limited to, communication that is spontaneous, face-to-face and familiarity with the communication partner.

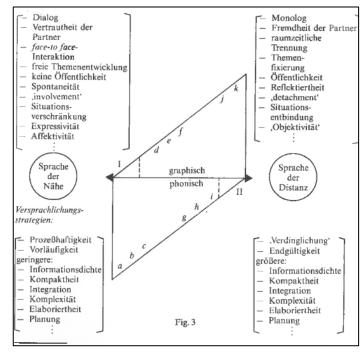


Figure 4. *Nähesprache and Distanzsprache* (Koch & Oesterreicher, 1985, p. 23)

Distanzsprache, or Sprache der Distanz, represents the opposite pole in that it depicts speech that includes, but is not limited to, communication that is detached, objective, unfamiliar, fixed topic, etc. Referring to figure 3 and figure 4, an intimate conversation is thus representative of spoken language, that is also conceptually representative of orality. The dynamic of the speakers is one of familiarity and closeness, and the speech can be assigned the label of Nähesprache.

The opposite can be said of administrative regulation texts. There is great distance between the speakers, both in terms of familiarity and proximity. It is also not a message that can be communicated conceptually orally due to the very nature of the text. It can be assigned as being conceptually representative of literacy, while being medially spoken and thus belongs to Distanzsprache. Using these parameters: medium, concept and distance-proximity, a more detail analysis of language is possible.

4. Styles and Registers

A speaker's linguistic choices often reveals information about their social and geographical background (Bieswanger & Becker, 2008). Registers, or styles, can be loosely defined as:

the function of language in a particular situation and the consideration of such factors as addressee, topic, location and the interactional goal rather than background

of the speaker. The exact definition of style and register is difficult....A common distinction is that style refers to the level of formality of an utterance or a text, whereas register refers to the choice of vocabulary in an utterance or a text (Bieswanger & Becker, 2008, p. 187).

Styles and registers are instrumental in determining literacy and orality since understanding how and when these registers are used will allow for better identification of literacy and orality in written language. Certain registers and styles are generally realized in specific situations akin to those presented in figure 3 and figure 4. The following sub-chapters depict specific French registers and how they map to conceptual discourse.

4.1. Le Français

French was historically seen as having a single register. This is not in the sense that it there was no variation, but rather, that there was one and

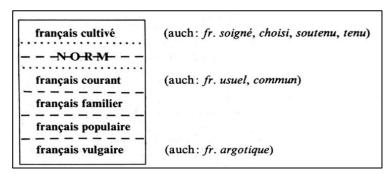


Figure 5. French Registers (Müller, 1975, p. 184)

only one correct way of using the French language referred to as *bon usage* (Müller, 1975). *Mauvais usage*, i.e., poor usage and *dites... ne dites pas, i.e.*, say this, not that, dictated the correct usage of French for most of French language history (Müller, 1975). This was in part due to the academic body, Académie Française, who has been the governing body of the French language since its establishment in the 17th century (Müller, 1975).

Nevertheless, it is not necessarily feasible to entirely dictate what speakers of any given language do or say as this is directly antithetically to a defining character of language construct which is that languages are in a constant state of change (Müller, 1975; Stein, 2008). This led to the development of various French registers as seen in figure 5 (Müller, 1975; Stein, 2008). French registers are classified as *français cultivé*, *français familier*, *français populaire*, *français vulgaire*, *français argotique* and *français technique* (Müller, 1975; Stein 2014).

4.2. Français Cultivé

Français cultivé, or FC, is often viewed in positive light and seen as the register that one should try to replicate seeing as this register is considered the highest register Müller, 1975). It should not be used in banal or informal situations, otherwise the speaker risks being seen as pedantic and pretentious (Müller, 1975). It is used in official or ceremonial situations (Müller, 1975).

The most prominent feature of this register is the phonological component. It tends to consequently conserve sounds that are no longer used in the other registers (Müller, 1975). This includes such as phonetic opposition of certain sounds, the pronunciation of the schwa at the end of phonological words and more rigid syllable structure. This has to do with the desire to retain the literary tradition, which is often dependent on such archaisms (Müller, 1975).

Certain verb tenses such *passé simple, passé antérieur, subjonctif imparfait* or verbal constructs such as *inversion* are characteristic of this register. The strict adherence to proper negation e.g., *ne...pas, ne...point, ne...guère* often appears with these verbal constructions (Müller, 1975).

It is often viewed as being representative of literacy as it retains the previously mentioned grammatical features which are no longer used in contemporary speech either conceptually or medially (Müller, 1975). Whether spoken or written, it is therefore considered artificial in the sense as it a controlled process heavily reliant on proper word choice, intonation and lengthy, detailed sentences (Müller, 1975).

4.3. Français Familier

Francais familier, or FF, is a qualitative register that is often used in informal situations such as with family, job, daily routine, acquaintances and people from one's inner social circle (Müller, 1975). It is a register that is indifferent to the social standing of the speaker, but it is used more frequently by those who have profited from a higher education than those who have not (Müller, 1975).

It is spontaneous in nature, and this is reflected in the fact that there is not a lot of emphasis placed on proper enunciation (Müller, 1975). This spontaneity is most likely since FF, and français populaire by extension, are directly descended from Vulgar Latin,

which itself was primarily a spoken register of Latin, both medially as well as conceptually (Müller, 1975).

Statements and questions are generally formed through falling and rising intonation, respectively, even though questions using *est-ce que* are possible (Müller, 1975). The doubling of pronouns or referents e.g., moi je, ton père il, etc. is characteristic of FF and high use of topicalization e.g., Cet homme, je l'ai vu très souvent (Müller, 1975).

It makes high use of suffixes to denote agents and actors in speech context e.g., chançard, gueulard, motard. This also includes the diminutive suffixes such as -et, ette, ot, etc. Reduplication is not only present among pronouns, but in nouns as well e.g., fla-fla, ronron, kif-kif (Müller, 1975).

Due to its spontaneous nature, speakers tend to avoid overly complex expressions when communicating strong feelings. This leads to a high number of simplified expressions, and atypically using adverbs as intensifiers (Müller, 1975). The register is often consigned to orality as it signalizes a nonchalant attitude and, as the name implies, a familiar atmosphere.

4.4. Français Populaire

Français populaire, or FP, is considered neither proper nor good French as it does not meet the requirements set by the norms or bon usage (Müller, 1975). Since it differs quite drastically from FC, it is often considered to be a language within a language congruence (Müller, 1975). This is because it is not consistent with FC, but rather within itself and presents grammar and orthography that while deviant, are internally consistent. It, along with FF, arose as a language of the people, meaning those who belonged to neither clergy nor nobility and whose speech was more commonly referred to as *lanuage du peuple* (Müller, 1975). In classifying it as such, FP is representative of orality.

Since communication is more important than grammatical correctness for speakers of this register, FP tends to forgo the linguistic norms (Müller, 1975). Verbal phrases are often formed without their corresponding personal pronouns (Müller, 1975). The appropriate auxiliary verbs, *avoir* and *être*, are used interchangeably, nominal congruence with respect to gender and number are either ignored or forgotten (Müller, 1975). The subjunctif is only employed when a strong desire s expressed as would be

the case with *vouloir*. Relative pronouns and conjunctions involving *que* tend to have a higher frequency for variability (Müller, 1975).

There is strong preference for neglecting the spelling, especially when the message is clear due to morphology. The most prominent example of this is the willingness to drop the ne of ne...pas (Müller, 1975). The lexicon does not differ in form from FC, but rather in usage, i.e., that speakers use the same words, but differently, which leads to expressions being hyperbolic and suggestive (Müller, 1975). A great deal of the words that occur within FP are known to most speakers of French; they only make up a small portion of the language. Most of the words that appear in FP are from the 19th and 20th century, which mainly stem from dialects and français vulgaire (Müller, 1975).

4.5. Français Vulgaire

Français vulgaire, or FV, is the lowest register both in terms of prestige and formality, and therefore conceptually oral in nature, is often grouped together with français argotique (Müller, 1975). The difference is that it and its components are generally known to all speakers of French, whereas français argotique is restricted to certain milieus (Müller, 1975). Interjections, expressions of displeasure and expletives are present throughout FV. It is avoided whenever possible as it is in direct opposition to social norms regarding etiquette. It is notable for its lack of scientific jargon, Latin loanwords, and euphemisms, but it is also incredibly adept at coining new words that employ the method of directness (Müller, 1975).

4.6. Français Argotique

Francais argotique or argot in its original form was meant to specify the speech patterns of marginal groups and that of professional jargon. A defining feature of argot is that the speaker is intentionally trying to distance themselves socially. At the same time, it is used as a way of identifying insiders and outsiders (Müller, 1975). This is usually the reason why argot is considered to be cryptic language (Stein, 2014).

Argot employs metonym to a high degree by applying descriptions of food to refer to the body. It also displays a high willingness to import loan words from dialects as well as other languages (Goudailler, 2002). Argot is highly representative of orality as the need to record speech in a written form was completely secondary. Due to the written aspect of language not being important, argot is relatively unstable (Müller, 1975). The extreme

degree to which argot changes is also a defining feature (Goudailler, 2002). This is because it reflects the period in which the speakers live and not the continuing of a linguistic tradition (Stein, 2014).

4.7. Français Technique

Français technique can be used to explain theoretical concepts to those who are from the same field, or a reduction in complexity is introduced i.e., vulgarization (Müller, 1975). This makes it more readily available to those who are not from a specific scientific field. A defining trait of it is the need to develop new terminology as the field of science is ever growing. This is done using complex use of morphological constructions (Müller, 1975).

The high influx of new words also come from English, which is a point of contention with those working with français technique, but often French words are substituted to combat this (Stein, 2014). The syntax and vocabulary are quite rigid, more so than that of FC, since precision in scientific fields is key. The syntactical structures are not per se complex, but it displays a high level of words that express causality which is to be expected as the goal is scientific in nature and conceptually literal.

4.8. Combining Registers and Discourse

Literacy and orality represent the binary feature set that is to be assessed. As the medium is apparent from the textual nature of the data set, it is assumed then that when the textual and medial discourse overlap, they represent literacy. If they are to diverge, then they represent orality. Therefore, it is possible to group the registers in a manner akin to figure 2 as presented by Koch and Oesterreicher (1985):

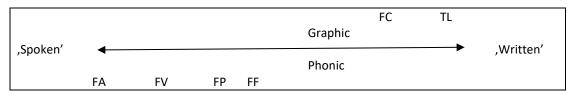
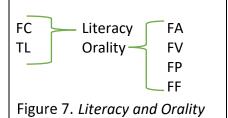


Figure 6. Registers According to Literacy and Orality

By grouping the registers in this manner, it is easier to ascertain where FRP and FRÉ overlap medially and conceptually. This graph can be further refined to allow them to be mapped to the



conceptual as seen in figure 7. Registers by their very nature represent different conceptual discourse types.

There is a lot of variation and overlap between the respective registers. So, it would not be reasonable or feasible to train a model to recognize the individual registers. However, by extracting characteristics and criteria from each class and grouping them according to their discourse type, it is possible to fit a model with criteria that allows it to automatically recognize literacy and orality.

5. The French Language Corpora

French is not a monolith, but a language that is spoken across many domains, age groups, countries (Stein, 2014; Müller 1975). Whether a native speaker of Metropolitan French, second-language speaker or speaker of given French, this variation is present in France as well as outside of it (Stein, 2014). This poses a challenge of sorts since what is of representative of conceptual discourse is to some extent dependent on the local and personal understanding of the language (Bader, 2002). Due to this, some concessions and compromises must be made for the subsequent chapters to be sound.

First and foremost, the object language here in question is that of Metropolitan French, which is contemporary French as spoken in France. The methods and reasoning will therefore apply to this variant of French. However, there is no feasible way to know if a speaker is completely in line with this standard and the aforementioned registers and styles. Since the internet is an open platform, and not bound to geographical constraints, it is plausible that speakers of other varieties have partaken in the conversations.

Finally, the data records stem from ca. 2000-2020 and can therefore only accurately encapsulate and illustrate the language at this stage. Of course, the age of each speaker would allow for an analysis that could potentially stretch further back into the past. However, no assumptions can or will be made about the language state before 2000 or projects about the language beyond 2020 as this would be purely conjecture.

5.1. Data Sets

There are three primary data sets that will be the focus of the linguistic analysis: eBay petites annonces, or EPA, (Gerstenberg & Hewett, 2019), CMR-wikiconflits, which will

be referred as Wikiconflits, (Poudat et al., 2015) and 88milsms, which will be referred to as SMS corpus (Panckhurst, 2016).

The EPA corpus contain online listings from the online auction platform, eBay and it was compiled by the department of Romance studies at the University of Potsdam with collection of around 1256 petites annonces which are split across four sub-corpora (Gerstenberg & Hewett, 2019). The first three sub-corpora deal with housing, vehicles, clothing, computer, telephones, children, collections and leisure, while the last corpus deals with professional activities e.g., stocks, shops, shipping (Gerstenberg & Hewett, 2019).

Wikiconflits contains discussions about IQ consisting of around 52 participants, 170 contributions and 20,000 tokens. As is often the case with sites like Wikipedia, the information presented may not be factually correct (Poudat, Kun et al., 2015). This does not necessarily pose a problem as the accuracy of the information is irrelevant with respect to its literacy and orality.

The SMS corpus is a collection of more than 88,000 SMS messages that were collected from speakers in the Montpellier area in France. To comply with French data protection guidelines, the data had already been anonymized by Panckhurst et. al (2014). The SMS donors were asked to participate in a questionnaire, about the languages they speak, their telephone number, their profession, how they communicate through SMS, the frequency of their communication and what their opinions of SMS communication are (Panckhurst, 2016).

The selection of the corpora was done in such a way as to provide three instances in which literacy and orality could appear. First and foremost, the SMS corpus are generally forms of informal communication and because of this, they should contain data that is mostly representative of orality (Bader, 2002). Secondly, the wikiconflits documents contain discussions that generally relate to scientific and official matters (Poudat et al., 2015). Therefore, it should fall more on the literal scale. As the eBay texts are combination of both orality and literacy, they should fall somewhere in between the other two corpora in terms of the conceptual discourse.

5.2. Pre-processing

All the corpora used in this research were created with the goal of computational linguistic analysis in mind (Gerstenberg & Hewett, 2019; Panckhurst et al., 2014; Poudat et al., 2015). Therefore, the data has been annotated and changed as little as possible by the respective institutions. This means that processes such as sentiment analysis, POS-tagging, tokenization are possible without interference from foreign analysis.

All the data sets are available in the .xml format, and contains markers to identify author, date, time and title of the post. The eBay corpus has been tagged with respect to typical features of ad postings such as abbreviations, misspellings, marketing language, slang, proper nouns and emoticons. Before the individual entries could be properly processed, the corpus had to be first sub-divided. The other two data sets, Wikiconflits and SMS, were already in one homogenous corpus and sub-division was therefore not necessary. However, all three of the data sets were then equally divided into three parts: development, training and test data sets.

Since files were in an .xml format, it was not possible to directly access the text, but rather through their respective tags. This was done by parsing them via .xml tags using the python module *beautifulsoup*. Once the textual data was exposed, the respective entries were tokenized into their respective sentences using a custom tokenizer that uses regular expressions to identify the end of the sentences. Subsequently, information related to parts of speech, morphological and syntactical dependencies as well as tokens were ascertained from the sentences by using *Spacy*.

6. Methodology

6.1. Classification Criteria

The methodology involves using a probabilistic algorithm to recognize literacy and orality in texts. However, before this can be done, training data must be ascertained. Due to the lack of known or adequate training data, another classification system must be employed by which a training data base can be built. From this database, probabilities can be calculated, and the conceptual discourse type of a given text can be made known.

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Various researchers (Bader, 2002; Ortmann & Dipper, 2019; Rehm, 2002) have provided a plethora of criteria by which one can automatically identify literacy and orality in discourse. These criteria focus on creating a system which is to be linguistically and chronologically independent. However, since French data is being classified, characteristics of the French registers were taken into consideration when developing the classification criteria. Based on different researchers (Bader, 2002; Ortmann & Dipper, 2019; Rehm, 2002), two distinct classification systems have been created as seen in table 1 and in table 2.

Variable Descri	ption	Point Amount
SEN_LEN	Sentence Length	The length of the sentence in character length
AVG_WORD_LEN	Average word length	The length of the average word length
THIRD_PERSON_EXPL	Dummy Subjects	The number of dummy subjects
NOM_SUBJ	Sentence Length	How often nominal subjects occur
PRES_TENSE	Present tense verbs	The number of present tense verbs
ABBR_NO_VOWEL	Abbreviations without vowels	Count of abbreviations without vowels
NP_VB_RATIO	Noun to verb ration	Noun count plus verb count
LOW_VERB_HIGH_ADJ	Low number of numbs, but high number of adjectives	Verb and adjective count
CCONJ_VB_RATIO	More coordinating conjunctions than verbs	Coordinating conjuct plus verb count
SHORT_SEN_LENGTH_PRESEN CE_OF_NUMBERS	Short sentences that consist of only numbers	Only one point

Table 1. Classification Criteria for Literacy

Variable	Description	Point Amount
SEN_LEN	Sentence Length	The length of the sentence in character length
AVG_WORD_LEN	Average word length	The length of the average word length
VERB_SEN_LEN_RATIO	Short sentences without verbs, high number of pronouns	The number of verbs and pronouns that occur within the sentences
WORD_REDUPLICATION	Occurrence of a word more than once in a text.	The number of words that occur more than once
PRES_TENSE	Present tense verbs	The number of present tense verbs
HIGH_PUNCTION	High use of punctuation	The number of punctation symbols
MULTI_CHAR_REDUPLICAT ION	Using the same character multiple times	The number of symbols that occur more than once
WORD_WORD_REDUPLICA TION	Using the same word back-to-back	The number of times a word is used more than once back-to-back
ALL_CAPS	All caps	Words written in all caps
ISOLATED_VERBS	Only verbs in a sentence	The length of the sentence
EMOTIOCONS	The usage of emoticons in a sentence	The number of emoticons used in a sentence
ABBR	Abbreviations and acronyms	The number of abbreviations and acronyms as they occur in the text.

Table 2. Classification Criteria for Orality

A document, i.e., a sentence is automatically analyzed according to both classification criteria. If a given criterion for a sentence is true, then it receives points equal to the respective category as specified in table 1 and table 2. At the end of the analysis, two scores will have been calculated. The sums of the respective scores are then compared. The feature of the higher score will then be assigned to a document. This means that if sentence receives more point with respect to orality, then the sentence will be classified as such and vice-versa.

6.2. Bayes' Theorem

An efficient and well-known method of classifying a document is done using a group of classifiers known as naïve Bayes classifiers with multinomial and Bernoulli naïve Bayes classifiers being among the most common (Jurafsky & Martin, 2020). The main difference between the two is that Bernoulli naïve Bayes models the presence or absence of features, whereas multinomial naïve Bayes counts the number of times a given feature occur (Jurafsky & Martin, 2020). They work well with binary classification and are most often employed in sentiment analysis, spam detection and authenticating authorship (Jurafsky & Martin, 2020). The following explanation applies to the multinomial Bayes. The naïve Bayes' algorithm is a conditional probabilistic algorithm that is first and foremost based on the Bayes' theorem which is as seen in equation 1.

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}$$
Equation 1. Bayes' Theorem

(Carstensen et al., 2010, p. 122)

P represents the probability of an event with A and B representing two distinct events. P(A|B) is the probability of A given B (Carstensen et al., 2010). Since Bayes' theorem is flexible, the events can be swapped as seen in equation 2.

$$P(B|A) = \frac{P(A|B) \cdot P(B)}{P(A)}$$
Equation 2. Bayes' Theorem Reversed
(Manning & Schütze, 1999)

P(A), as seen in equation 2, the normalizing constant guarantees that the equation has a probabilistic aspect to it (Manning & Schütze, 1999) . P(A) can be broken down into its individual elements as it is the combined probability of all events and is calculated as seen in equation 3.

$$P(A \cap B) + P(A \cap \overline{B})$$

 $P(A|B) \cdot P(B) + P(A|\overline{B}) \cdot P(\overline{B})$
Equation 3. Normalizing Constant
(Manning & Schütze, 1999, p. 43)

 \overline{B} represents not B, with \cap being the intersect between two respective events.

6.3. Naïve Bayes as a Classifier

A document classifier can be created by using Bayes' theorem as a basis. To make the explanation more suitable for text classifications, the variables have been changed, as seen in equation 4, but the base form of Bayes' theorem remains intact.

$$\hat{c} = \underset{c \in C}{argmax} P(c|d) = \underset{c \in C}{argmax} = \frac{P(d|c) \cdot P(c)}{P(d)}$$
Equation 4. Naïve Bayes' Classifier
(Jurafsky & Martin, 2020, p. 57)

 \hat{c} , the estimation of the correct class, represents the maximum posterior probability with d being the documents out of all classes $c \in C$ (Jurafsky & Martin, 2020). However, as is often the case with NLP tasks, only the maximum argument which consists of the product of the likelihood and prior probability (Jurafsky & Martin, 2020). Both must first be computed as presented in equation 5.

$$argmax_B P(B|A) = \frac{P(A|B) \cdot P(B)}{P(A)} = argmax_B(A|B) \cdot P(B)$$

$$Equation 5. Argmax$$
(Manning & Schütze, 1999, p. 43)

Equation can then be converted be in line with the naïve Bayes' classifier, which produces the following as presented in equation 6.

$$\hat{c} = \mathop{argmax}_{c \in C} P(c|d) = \mathop{argmax}_{c \in C} P(d|c) \cdot P(c)$$

Equation 6. Argmax of Classification
(Jurafsky & Martin, 2020, p. 58)

In equation 6, there are two main probabilities that must first be ascertained must first be computed as seen in equation 7.

$$\hat{c} = \mathop{argmax}_{c \in \mathcal{C}} \stackrel{Liklihood}{\widehat{P(d|c)}} \cdot \stackrel{prior}{\widehat{P(c)}}$$
Equation 7. Model Probabilities
(Jurafsky & Martin, 2020, p. 58)

P(c) is the prior probability of a given class. The likelihood, as in equation 8, is assumed to be in line with the bag-of-words principle, which states that the position of

the words within a given text is irrelevant as only number of times a word occurs is important (Jurafsky & Martin, 2020).

$$\hat{c} = \underset{c \in C}{argmax} P(c|d) = \overbrace{P(f_1, f_2, \dots, f_n|c)}^{Liklihood} \cdot \overbrace{P(c)}^{prior}$$

$$Equation \ 8. \ Likelihood$$
(Jurafsky & Martin, 2020, p. 58)

Thus, the naïve Bayes assumes that occurrence of the features, but not their position as laid out in equation 9:

$$P(f_1, f_2, ..., f_n | c) = P(f_1 | c) \cdot P(f_2 | c) \cdot ... \cdot P(f_n | c)$$

Equation 9. Composition of Likelihood
(Jurafsky & Martin, 2020, p. 58)

By applying equation 9, the equation 10 results.

$$C_{NB} = \underset{c \in C}{argmax} P(c) \prod_{f \in F} P(f | c)$$

Equation 10. Argmax of Likelihood
(Jurafsky & Martin, 2020, p. 58)

Equation 10 is a condensed form of equation 9. Equation states that a product of all likelihood within a given text must be computed. To apply formula 10, it is only necessary to traverse all words in each document as detailed in equation 11

$$C_{NB} = \underset{c \in C}{argmax} P(c) \prod_{i \in positions} P(w_i|c)$$

Equation 11. Calculating Argmax
(Jurafsky & Martin, 2020, p. 58)

It is first necessary to train the model by calculating the probabilities of P(c) and P(f_i | c). This is done by using the frequencies in the training data to ascertain the MLE as presented in equation 12.

$$\hat{P}_{(c)}=rac{N_c}{N_{doc}}$$
Equation 12. MLE
(Jurafsky & Martin, 2020, p. 59)

Equation 12 states that for a given number of documents, how many times does a given class occur within this document. Finally, to compute $P(f_i | c)$ as $P(w_i | c)$, the

frequency of a given word occurring within a given class is calculated, then divided by the sum of how often words within a given class occur as presented in equation 13.

$$\widehat{P}(W_i|c) = rac{count\ (wi,c)}{\sum_{w \in V} count\ (w,c)}$$
Equation 13. Calculating Prior Probability
(Jurafsky & Martin, 2020, p. 59)

The problem here comes when a given word does not occur within a certain class, this means that the effective frequency is zero. To remedy this problem, a smoothing algorithm must be applied. There are many methods from which one can choose such as La-Place, Good Turing, held-out, etc. (Jurafsky & Martin, 2020). However, the one used in this paper is based on that of Ng (1997):

$$P\left(W_i|C_n\right) = \frac{C\left(w_n\right)}{N^2}$$

Equation 13. Ng Smoothing

As stated in equation 13, with all other parameters being equal, *N* here represents the amount of training data from a given corpus, the amount of which must be squared. This formula must be applied for each respective class in the corpus.

6.4. A Worked Example

For sake of simplicity, it is assumed in the following corpus, as seen in table 3, that the sentences have the following features as listed in the feature column. They have not

	Feature	Document
Training		
	ORAL	Vous dites quoi ?
	ORAL	Faut partir parce qu' il pleut .
	ORAL	Je n' sais pas .
	LIT	Il faut partir, car il pleut .
	LIT	Elle m' a dit que j' étais une imbécile .
Test	?	Vous dites imbécile

Table 3. Mini corpus
Examples taken from Müller (1975, p.185)

necessarily been analyzed using the classification criteria as specified in table 1 and table 2. Therefore, these sentences do not necessarily represent the conceptual features assigned to them. Using these sentences as a small training corpus, it is possible to ascertain the most probabilistic classification of a sentence the *vous dites imbécile*.

	ORAL LIT	
Prior Probability	.60	.40
Smoothing	.12	.08

Table 4. Classification Values

	ORAL	LIT
Vous	0.3	0.08
Dites	0.3	0.08
Imbéciile	.12	0.05
Prior	0.60	.40
Probabiltiy		
	0.00798	0.00128

Table 5. Classification Assignment

First, the feature count must be extracted from the corpus in table 1. There are 5 documents in total, with 3 being ORAL and 2 being LIT. With this information, equation 12 and equation 13 can be applied. They produce the following results as seen in table 4. Combined with the values in table 4, the MLE values for the respective tokens can be calculated according to equation 13. The results of which are present in table 6.

The final step is simply to traverse the sentence as specified in equation 11 by retrieving the

Token	LIT (ORAL
•	0.66	1.0
	0.12	0.5
?	0.33	0.08
Elle	0.12	0.5
Faut	0.33	0.08
П	0.12	0.5
Je	0.33	0.08
Vous	0.33	0.08
а	0.12	0.5
car	0.12	0.5
dit	0.12	0.5
dites	0.33	0.08
faut	0.12	0.5
il	0.33	0.5
imbécile	0.12	0.5
j'	0.12	0.5
m'	0.12	0.5
n'	0.33	0.08
parce	0.33	0.08
partir	0.33	0.5
pas	0.33	0.08
pleut	0.33	0.5
que	0.12	0.5
quoi	0.33	0.08
qu'	0.33	0.08
sais	0.33	0.08
une	0.12	0.5
étais	0.12	0.5
Table 6.	MLE	Values

respective values from table 6 and multiplying the respective products by their respective prior probabilities. The result, as seen in table 5, shows that the sentence is most likely ORAL based on the corpus as presented above.

7. System Evaluation

7.1. Developmental Overhead

As was the case with the corpora used in this project, most linguistic data is typically stored in an .xml format. The training files created by the program were saved as .csv files. Finally, the program had to also be able to accept .txt files as well as strings as these would be the most common way of training and inputting data into the system. The

program is dynamic and allows for user input which required the implementation of error correction and prevention.

The optimization of the program was done in two main steps: development, and training, with testing being done in the last phase. The training of the program varies depending on the amount of data being input into the system and the system resources.

The classification criteria used to create training data could theoretically be retrained to recognize any language supported by Spacy. As for applying the algorithm to a domain other than literacy and orality, this would also heavily depend on the training data being supplied to the naïve Bayes.

Naïve Bayes is in of itself a relatively flexible algorithm that can be applied to a whole host of classification tasks. Therefore, if the program were supplied with slightly different parameters and training data, it could be restructured to recognize data with other binary classifications in mind e.g., positive vs. negative, spam vs. not spam, detection between two languages, positive vs. impolite, etc. The limitation does not lie necessarily within the program, but rather within the training data made available to the naïve Bayes.

7.2. Classification Sets and Naïve Bayes

The original scoring system was to assign one point if a criterion in any given classification was met. However, this proved to be ineffective, as it treated all criteria equally. This often caused the sentences to be either assigned to the wrong category or all of them to be assigned to only one category. The solution to this entailed weighting the criteria according to the importance and prevalence of the data set as in table 1 and table 2.

The first classification criteria, as seen in table 1, considered features that were prevalent throughout texts which often expressed a high degree of literacy. These were weighted according to their prevalence and importance. Using these criteria, training data was created, labeled and then evaluated. The results of this evaluation can be seen in table 7.

	Values	
	(in Percent)	
Accuracy	94	
Error Rate	.05	
Precision	1	
Recall	69	
F-Score	82	

Table 7. Evaluation of Training Classification Criteria for Literacy

A second classification criteria set, table 2, was created that mirrored the first classification set, table 1, to a certain extent, but with slightly modified parameters and considered factors that often occurred in French texts expressing orality. This classification set was then tested and evaluated, the results of which can be seen in table 8.

	Values (in Percent)
Accuracy	91
Error Rate	0.08
Precision	0.77
Recall	.31
F-Score	0,81

Table 8. Evaluation of Classification of Orality

Using a separate sub dataset within the development corpus, a training database was created. This database was then made available to the the naïve bayes algorithm. The results of this process can be seen in table 9.

The results of table 7, table 8 and table 9 were ascertained by manually creating a gold file for the respective files.

	Values (in Percent)
Accuracy	94
Error Rate	0,05
Precision	1,0
Recall	0,88
F-Score	0,936
Cross	78
Validation	

Table 9. Naïve Bayes
Evaluation

7.3. Sentence Tokenizer

Since the data is non-standard, it was not always clear which sentences should be parsed and where they should be parsed. Data from all three domains often lacked any meaningful punctuation or punctuation was used incorrectly in that there was often reduplication of certain symbols to create an emphatic impression. This was

Accuracy (in
Percent)
100%
95%
94%
Sentence
n evaluation

especially true of the SMS corpus, where conservative definitions of sentences do not apply. This includes, but is not limited to, beginning a sentence with capital letters or ending a sentence with punction such as . ! or ? (Bader, 2002; Rehm, 2002).

This resulted in sentences that were sometimes too long or too short, which skewed the results. Long sentences could not be parsed without syntactically and semantically analyzing the sentence. Due to this, some sentences were added together that should have been split by the author. The reverse, however, cannot necessarily be said. It was apparent from the data, such as eBay online postings, that bullet points, rather than sentences were the intent of the author. Therefore, the decision was made to include

bullet points as sentence markers as well. Dates and times were also seen as marking the end of sentences as many entries only contained such information.

There was no explicit rule that split sentences containing only numbers but was rather a result of the way the authors formulated their sentences. With this information in mind, the accuracy as presented in table 10, is to be seen as indicator that the algorithm parses the sentences correctly, but not perfectly. The results can vary depending on the information given to the sentence parsing algorithm.

7.4. Spacy Module

The spacy module was used for tokenization, part-of-speech tagging, syntactical dependencies and assessing morphology. Tokens included punctuation and non-letter symbols as they were often essential in emoticons

	Projected Accuracy	System Accuracy		
Tokenization	100	100		
POS	93	93%		
Dependency	96	99%		
Morphology	90	93%		
Table 11. Spacy Accuracy				

and reduplication. Therefore, no changes were made to the data to make it easier to be processed by Spacy as the linguistic nature of the data was to remain as unaltered as possible.

Fr_core_news_sm (n.d.) states that tokenization, part-of-speech tagging, syntactical dependency tagging, and morphology tagging have an accuracy of 100%, 93%, 96% and 90% respectively. These values align with the actual values pulled from a small data section of data from each development corpus set with a small deviation, the results of which can be seen in table 11.

The Wikiconflits and eBay data were easily processed by spacy with minimal errors. This was due in part to the authors following orthographic norms and not using non-standard language excessively. A challenge posed to Spacy was that users of the SMS chats often had incorrect spellings, made high use of emoticons or created new unknown abbreviations. However, emoticons were classified as punctuation, rather than as emoticons. This caused Spacy to perform poorly compared to the other data sets, but the values were still with an acceptable range.

8. Results¹

The number of sentences and tokens were not distributed equally among all three of the original corpora with the SMS corpus being the largest and the wikiconflits being the smallest corpora. Therefore, it was ensured that the development and training would only entail a small portion of each data set to ensure that there was an even distribution and the maximum number of documents extracted from each corpus was kept to a minimum.

8.1. Developmental Basis

Originally, a French-based classification set was meant to gauge the reliability of the language independent classification criteria as seen in table 1 and table 2. The validity of the language independent classification criteria would be weighed against the language-dependent criteria set. However, this proved to be extremely ineffective since there were not enough unique words and criteria to push a sentence into one category over another. The result of this was that sentences were either wrongly classified or the number of unknown sentences was extremely high.

The second problem voids this solution as too many features were being deleted from a sentence which caused it to be unrecognizable by the language-independent classification. The first classification relied heavily on sentence, word length, reduplication and emoticons, which are crucial for determining literacy and orality. Therefore, the features that would have been present in the other system were generalized and incorporated into the second classification system. This ultimately data results that were too imbalanced and not reliable for evaluation.

The developmental phase of this project was therefore crucial since there were no French training data and criteria available by which it was possible to ascertain literacy and orality in datasets. Using a combination of criteria proposed by various authors (Bader, 2002; Koch & Oesterreicher, 1985; Ortmann and Dipper, 2019; Rehm 2002), it was possible to develop and refine a system by which literacy and orality could automatically be assigned to sentences.

¹ The sentences that do not appear in the following results are not accounted for since they were classified as being unknown. This means that it could not be determined if they were representative of literacy or orality

Problems that were touched upon earlier were present throughout the eBay and SMS corpora which was that the data was non-standard, this made the classification quite difficult as there was no way to guarantee uniformity. This was compounded by the fact that French is not exclusively used in all the data sets. In the SMS and eBay corpus, there were traces of German and English since postings and conversation were on a national, and not always a local scale.

8.2. Development phase

Using the scoring system with Wiki and SMS as training data, data was labeled according to the classification sets mentioned in table 1 and table 2.

	Corpus ID	Sentences	Tokens	Documents	LIT	ORAL
Wiki	wikiconflits_0_53	345	6766	53	234	110
SMS	sms 0 29507	349	34454	150	129	218

Table 12. Development Results of the Classification Data

While creating the training data, the most relevant classification criteria were retrieved for Wikiconflits, table 13, and for SMS, table 14 respectively.

Feature	Classification Criteria
LIT	SEN_LEN
LIT	AVG_WORD_LEN
LIT	NP_VB_RATIO
ORAL	AVG_WORD_LENGTH
ORAL	MULTI_CHAR_REDUPLI CATION
ORAL	SEN_LEN

Table 13. Top Development Classification Criteria for Wikiconflits

Classification Criteria
SEN_LEN
NP_VB_RATIO
PRES_TENSE
SEN_LEN
ALL_CAPS
AVG_WORD_LENGTH

Table 14. Top Development Classification Criteria for SMS

Sentence length, noun-to-verb-ratio, and average word length are decisive in determining the feature for the training data set for both corpora. After having acquired the training data using the scoring system, it was entered into the naïve Bayes algorithm and trained on it. Then, all four of the eBay corpora were used as testing corpora. The results of table 15 show that all four of the eBay sub-corpora display a high rate of literacy with a low rate of orality.

	Corpus Id	Tokens	Sentences	Documents	LIT	ORAL
еВау	ebayfr-	4929	380	100	361	8
	e05p_0_100					
еВау	ebayfr-	6195	317	100	312	3
	e17p_0_100					
еВау	ebayfr-	21184	1028	100	995	32
	e17xp_0_100					
еВау	ebayfr-	9321	563	100	551	9
	e18v_0_100					

Table 15. Naïve Bayes Development Results

Even though all contained 100 documents, the number of sentences and tokens contained within vary significantly. Despite this, they are uniform in the way literacy and orality are distributed across the data.

8.3. Training phase

After the development phase and with only slight modification to the data and criteria set, the model was then retrained using the same process on the second portion of the data without incorporating the results from the developmental phase. The modification included correcting errors in the code that would assign incorrect scores to the ratios.

The results of which mirror those of the development phase to a certain degree and can be seen in table 16. Wiki again displays a high level of literacy while SMS displays a high level of orality. As during the development phase, the top classification criteria were retrieved from and can be seen in table 17 and table 18.

	Corpus Id	Tokens	Sentences	Documents	LIT	ORAL
Wil	i sms_29508_59014	8226	463	52	303	160
SM	Wikiconflits_0_54_106	4138	458	255	140	317

Table 16. Training Results of the Classification Data

Feature	Classification Criteria
LIT	SEN_LEN
LIT	AVG_WORD_LEN
LIT	NP_VB_RATIO
ORAL	AVG_WORD_LENGTH
ORAL	MULTI_CHAR_REDUPLIC ATION
ORAL	SEN_LEN

Table 17. Top Training
Classification Criteria for Wikiconflits

Feature	Classification Criteria
LIT	NP_VB_RATIO
LIT	SEN_LEN
LIT	NOM_SUBJ
ORAL	SEN_LEN
ORAL	ALL_CAPS
ORAL	AVG_WORD_LENGTH

Table 18. Top Training Classification Criteria for SMS

These results do not differ from those of the development corpus. The process from the development phase was then repeated by retraining a new database with new training data created from the classification criteria. After that, the naïve bayes was then tested again on the eBay corpus data.

	Corpus Id	Tokens	Sentences	Documents	LIT	ORAL
еВау	ebayfr-	5225	315	100	283	32
	e05p_101_200					
еВау	ebayfr-	6242	373	100	337	36
	e17p_101_200					
еВау	ebayfr-	24477	1202	100	1112	89
	e17x_101_200					
еВау	ebayfr-	9784	542	100	503	39
	e18v_0_100					

Table 19. Naïve Bayes Training Results

The results of the training phase, as seen in table 19, mirror those of the development phase as well. The eBay corpora display a high level of literacy with a low level of orality.

8.4. Testing phase

Using the training data created during the training phases as described in 8.3, the naïve Bayes was trained to assess the literacy and orality of each corpus. The results of which can be seen in table 20.

	Corpus Id Tok	ens	Sentences	Documents	LIT	ORAL
еВау	ebayfr-e05p_201_ 300	4063	249	100	229	20
еВау	ebayfr-e17p_201_300	4680	275	100	254	21
еВау	ebayfr-e17x_201_300	1715 5	922	100	830	922
еВау	ebayfr-e18v_201_300	9824	588	100	5151	43
Wiki	wikiconflits_79_159	9172	487	53	441	46
SMS	sms_59015_88522	3523	342	250	293	49

Table 20. Naïve Bayes Testing Results

The biggest deviation in the testing results those of the SMS data which shows a high literacy and opposed to orality. Another anomaly is that the ebay 17x eBay corpus as it shows orality and literacy equally.

9. Discussion

Various authors (Bader, 2002; Koch & Oesterreicher 1985; Ortmann & Dipper, 2019; Rehm 2002) proposed methods and ideas that are directly related to literacy and orality. The use of a scoring system was essential as it provided more control and more speed with respect to building a necessary training data set. It might seem somewhat redundant to have a training data algorithm and a naïve Bayes in the same program. It could be rightfully said that having a naïve training algorithm would suffice as opposed to having a naïve Bayes and training algorithm. However, this problem could not be avoided as no reliable or accurate training data existed. Thus, a program to create training data and then train the naïve bayes was a necessity.

Nevertheless, there was an earnest attempt made at ascertaining reliable French examples of literacy and orality by developing a separate French classification set. One of the most reliable and well-known sources of information regarding French philology comes from Müller (1975). This was initially set to be the source of much contextual French information for the training data as well as the naïve Bayes. Despite the age of this work, much of the information contained within is still relevant to the French language. Many of the descriptions about literacy and orality that appeared within were essential in refining and rechecking the algorithms, defining sentence length and even developing a scoring system based on French.

Müller (1975) offers readers prototypical texts of the respective French registers that can be graphed to respective discourse types. Despite all of this, it was the quantity, and not the quality of the texts, that proved to be a hindrance with respect to training a naïve Bayes to recognize literacy and orality in French discourse data. Had more information been readily available by Müller (1975) or other similar sources, then less emphasis and time would have been placed on developing a scoring system.

The scoring system relied heavily on naïve assumptions that often proved to be correct. More points were given to sentences that are longer, and less to sentences that are shorter. This often created an imbalance and drowned out the other classification criteria such as, but not limited to, adverbs, pronouns, adjectives.

It was not uncommon for sentence length to be the decisive factor in determining literacy and orality. Sentences that were long tended to represent literacy as opposed

to orality. Upon manual inspection of the results, this turned out to be correct in most instances. This was not necessarily universally correct as sentence length was also highly dependent upon the user correctly using punctuation, which in turn was to be recognized by the sentence tokenizer. If the author of text incorrectly used punctuation, the sentence would be split prematurely and thus skewing the results.

This naïve approach poses a problem as it prevents the system from having a precise reason as to why a particular sentence is representative of orality and opposed to literacy. With that being said, the scoring system would benefit from having a more evenly distributed point and scoring system that is more fine-tuned to the French language.

It was initially hypothesized that Wiki documents would show the highest amount of literacy, and the lowest amount of orality. The SMS chats would be on the opposite end of this spectrum and display the highest amount of orality, whilst having the lowest amount of literacy. To strike a theoretical balance between the two corpora, the eBay corpus was chosen to serve as a control to be between the two corpora.

Using the eBay corpora as a control, the naïve Bayes was trained so that it could recognize sentences that it had not seen before. More documents were classified as literal than expected. This was due to the criteria seeing more of the data as being literal than oral and was thus these results transferred over to the naïve Bayes. Even taking this into account, eBay data is more along the lines of being representative of literacy and orality.

The unexpected high literacy in eBay data can be attributed to buyers and sellers using an imbalanced combination of both. The postings had to be of a literal quality to attract buys as literacy used in such business situations (Koch & Oesterreicher, 1985). That is to say that using it lends credence to the belief that one is being more serious and professional (Koch & Oesterreicher, 1985). However, some buyers did not want to exaggerate this and offset this discourse type by presenting part of their postings. A blend of the two was thus inevitable.

The wiki data showed a high level of orality, but this was to be expected as a lot of the discussions revolved around topics that were highly scientific and intellectual in nature. When orality did occur, then it was only in short bursts or uttering small statements.

The SMS chats were of a high orality quality, this was to be expected and extracting literality from these texts proved to be the most difficult. First, the authors of the documents were very familiar with one another, and this was reflected in the language used by them. There were a high number of pronouns, nouns, proper nouns and redacted names². The end of sentences was more often marked by capitalized words, in particular capitalized pronouns.

Typical punctuation such as periods, exclamation marks, question marks were used emphatically rather than syntactically. That is to say that they were more often employed to express orality, rather than to mark the end of a sentence. Finally, a lot of sentences lacked any coherent or predictable endings. This had the side-effect of the program classifying sentences as being literal when they were not, as long sentence length is a sign of literacy in the texts.

The main issue with the system is that it cannot necessarily tell why exactly a sentence is representative of literacy or orality with respect to the author's intent. This is the inherent issue in using a naïve Bayes to calculate such features. It simply takes what it has gathered from a training data set and then presents a result based on said data. However, it cannot give one insight into the thoughts of the author as to why one discourse type was preferred over the other.

In addition to that, the results were different than had initially been expected. This expectation was not based on a scoring system or probabilistic reasoning as was the case with Ortmann and Dipper (2019; 2020), but rather on the notion that these data sets must be inherently different due to the nature of their data.

SMS is interpersonal communication which generally brings along the characteristics of being representative of orality (Koch & Oesterreicher, 1985). Wikiconflits discussions are group discussions of a scientific quality and thus must most likely represent literacy (Koch & Oesterreicher, 1985). As for the eBay corpus, the buyer and seller were not necessarily in permanent and constant contact with one another, and this indicates discontinuous, asynchronous communication which is a sign of literacy (Ortmann & Dipper, 2019). The expectation was based on the notion that eBay posters creating their

² The names being redacted was part of the pre-processing done the respective institutions and was thus not part of this project.

postings would have more time to prepare and rehearse them and this preparation is often reflective of literacy (Koch & Oesterreicher, 1985; Ortmann & Dipper, 2019).

The classification of the registers, as seen in figure 6 and figure 7, were the catalyst for reaffirming the notions of Koch and Oesterreicher (1985) and Ortmann and Dipper (2019). There was not enough data provided by Müller (1975) to strictly rely on such sociolinguistic parameters. However, automatically recognizing the French registers was not the direct goal of the program. The ideal situation would have entailed having the program classify an utterance according to its register, which then could be graphed on a discourse type. This was indirectly done by having examined the registers, their properties and how they map to literacy and orality.

10. Conclusion

With all things being equal, the internet, and by extension digital communication, are still in their infancy. They provide a wealth of information that can be useful for linguistic analysis. This was the reason for wanting to use non-standard French language data in an electronic form.

The goal of this project was to assess literacy and orality in non-standard data. This was to be done using a naïve Bayes classifier which only works if it has training data from which it can learn. As there was no such data available, it was necessary to create a scoring to automatically and prototypically tag sentences that represented literacy and orality in French. Creating an algorithm that creates training data and then successively training a naïve Bayes allowed for insight into the nature of discourse information in non-standard French data.

The initial thought behind using the three corpora was that eBay would serve as the midway point SMS and Wikiconflict chats. However, this is false as the conceptual is often much more difficult to define and determine than the medial representation of language. Despite this initial set back, the nature of literacy and orality in non-standard data could be determined to a certain degree. The data shows that there is indeed a spectrum of literacy and orality within data and that the data, while it can represent a discourse, it cannot be entirely dictated by that. The most interesting point here was that the discourse type can be determined in a text using universal and general classification features as well as a naïve Bayes classifier.

The domains of the respective texts can offer up plausible reasons as to why certain discourse types were chosen as opposed to others. SMS being interpersonal communication, Wikiconflits being scientific in nature and eBay representing asynchronous communication. Despite only having speculative answers and having minor setbacks, it is worth noting that the results line up with previous research and the assumed domains of the research types. More research and devotion to this topic would allow linguistic analysis to show as to why authors prefer one discourse type over another.

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Eigenständigkeitserklärung

I hereby declare that the work submitted is my own and that all passages and ideas that are not mine have been fully and properly acknowledged. I am aware that I will fail the entire course should I include passages and ideas from other sources and present them as if they were my own.

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Kamen, 14.08.2021

Christopher Michael Chandler