Straight Talk! - Automatic Recognition of Direct Speech in Nineteenth-century French Novels

Introduction

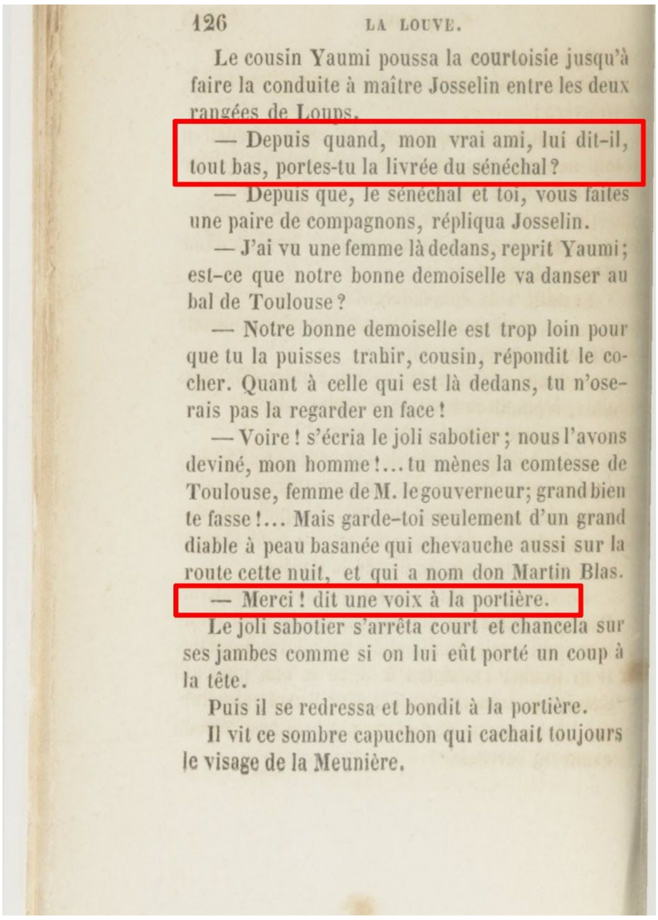
In fictional prose narrative such as novels and short stories, various forms of speech, thought, and writing representation are ubiquitous and have been studied in great detail in linguistics and literary studies. However, beyond quotation marks, what are linguistic markers of direct speech? And just how ubiquitous is direct speech really? Is there systematic variation in the amount of direct speech over time or across genres? Especially for the field of French literary history, where typography is not a reliable guide, we really don't know.

This is regrettable, because being able to quickly and automatically detect direct speech in large collections of literary narrative texts is highly desireable for many areas in literary studies. In the history of literary genres, this allows to observe distributions and evolutions of a fundamental, formal aspect of the novel on a large scale. In narratology, differentiating narrator from character speech is a precondition for more detailed analyses of narrator speech, e.g. with regard to text type (descriptive, narrative, argumentative text). And in authorship attribution, it hereby becomes possible to discard character speech from a set of novels and perform authorship attribution on the narrator speech only, something which may improve attribution.

Against this background, the work presented here addresses both the question of how to identify direct speech in French prose fiction and that of how prevalent direct speech is in different subgenres of the nineteenth-century French novel.

Aims and hypotheses

Our first aim has been to use machine learning to automatically identify direct character speech in a small collection of French-language fictional prose. This is less trivial than it seems to be since in the French typographical tradition, direct speech is usually not marked with opening and closing quotation marks (figure 1). Rather, a long hyphen usually indicates the beginning of direct speech, whereas the end is left unmarked. In figure 1, the first highlighted direct speech continues after the insertion revealing who has just spoken (“lui dit-il, tout bas,”; *he quietly said to him*). In the second example, the direct speech ends after the speaker has been indicated (“dit une voix à la portière”; *said a voice at the door*). Our hypothesis is that there are enough linguistic markers of direct speech to make it possible to identify it automatically and reliably (for an overview of such markers, see Durrer 1994).



126 LA LOUVE.

Le cousin Yaumi poussa la courtoisie jusqu'à faire la conduite à maître Josselin entre les deux rangées de Loups.

— Depuis quand, mon vrai ami, lui dit-il, tout bas, portes-tu la livrée du sénéchal ?

— Depuis que, le sénéchal et toi, vous faites une paire de compagnons, répliqua Josselin.

— J'ai vu une femme là dedans, reprit Yaumi ; est-ce que notre bonne demoiselle va danser au bal de Toulouse ?

— Notre bonne demoiselle est trop loin pour que tu la puisses trahir, cousin, répondit le cocher. Quant à celle qui est là dedans, tu n'oserais pas la regarder en face !

— Voire ! s'écria le joli sabotier ; nous l'avons deviné, mon homme !... tu mènes la comtesse de Toulouse, femme de M. le gouverneur ; grand bien te fasse !... Mais garde-toi seulement d'un grand diable à peau basanée qui chevauche aussi sur la route cette nuit, et qui a nom don Martin Blas.

— Merci ! dit une voix à la portière.

Le joli sabotier s'arrêta court et chancela sur ses jambes comme si on lui eût porté un coup à la tête.

Puis il se redressa et bondit à la portière.

Il vit ce sombre capuchon qui cachait toujours le visage de la Meunière.

Figure 1: Detail from Paul Féval, *La Louve*, 1857, p. 126 (Source: http://gallica.bnf.fr/ark:/12148/bpt6k6366934b).

Our second aim has been to use the best-performing algorithm to identify direct speech in a larger collection of French nineteenth-century novels and to study its distribution. Here, we hope to detect significant differences in the proportion of direct speech found in different novelistic subgenres. Research about other literary traditions supports this hypothesis (e.g. Allison et al. 2011).

State of the Art

Speech, thought and writing representation are common topics in narratology and stylistics (Genette 2008, Leech/Short 2007). Semino & Short's 2004 quantitative study finds that direct representation is clearly the most frequent type in their English fiction sub-corpus. Brunner 2015 confirms this trend for her corpus of German short narratives. Here, the percentage of sentences containing direct speech is about 35% and varies widely over different texts (2%-72%).

Frequently, speech representation recognition is an auxiliary step to other tasks, e.g. knowledge extraction or speaker recognition (Krestel at al. 2008, Elson & McKeown 2010, Iosif & Mishra 2014, Sarmento/Nunes 2009). Weiser & Watrin 2012 used a rule-based approach to extract unmarked quotations in French newspaper texts with success rates of 0.745-0.789. Brunner 2015 focuses on speech, thought and writing representation in German short literary narratives. Using machine learning with random forests, she reports an F1 score of 0.87 for direct speech in a sentence-based cross-validation.

Data

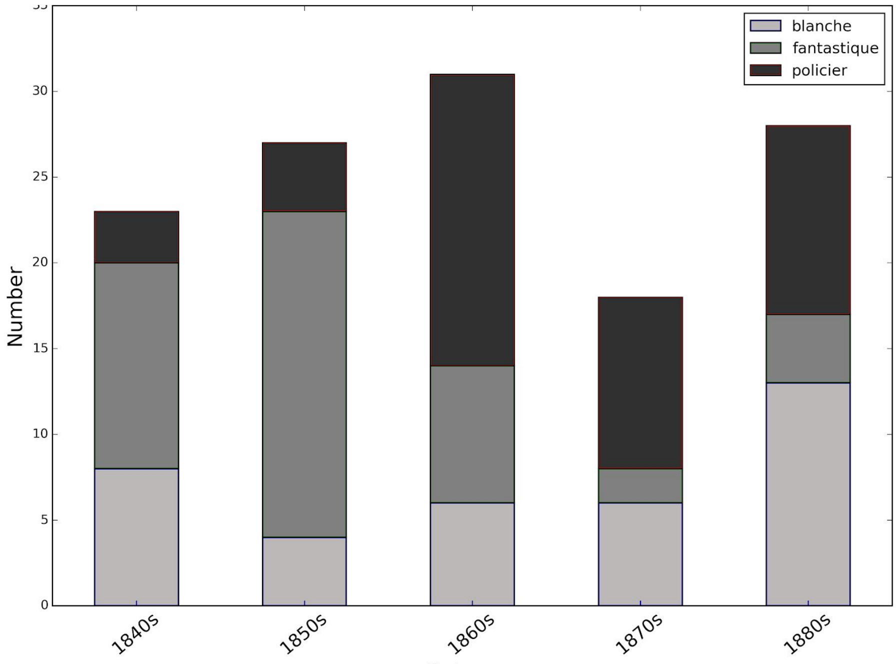


Figure 2: Distribution of novels per subgenre and decade.

Our text collection contains 127 French novels published between 1840 and 1889. Three generic subsets can be distinguished, each of which is represented by approximately 40 texts: general novelistic fiction (so-called ‘littérature blanche’) is contrasted with specific subgenres, crime fiction (‘policier’) and fantastic novels (see figure 2). The narrative perspective is largely heterodiegetic.

Methods

Manual Annotation

To obtain a gold standard, 40 chapters from 20 different novels were randomly chosen from the collection and annotated manually. 5734 sentences were marked as either containing direct speech or not containing any direct speech; the former also include mixed sentences.

Preprocessing

To prepare feature generation, preprocessing was performed, the pipeline consisting of the Stanford CoreNLP-Tokenizer and Sentence-Splitter, as well as the TreeTagger for POS-Tagging and Lemmatization.

Feature generation

We modeled 81 features which we believed to be useful cues for the classification task (see the annex for a ranked list). Features are generated on a sentence-based level and can be divided into different categories:

- Character-based: e.g. long hyphen marks, exclamation marks, question marks.
- Lexical: e.g. deictic expressions, interjections.
- Semantic: categories of verbs, from WordNet and the French equivalent WOLF: e.g. verbs of motion or perception.
- Morphological: e.g. part-of-speech, verb-tense, lemma.
- Syntactic features: e.g. number of commas, sentence length.

Classification

For the binary classification task (sentences containing vs. not containing direct speech), we used an annotation and classification framework developed by Markus Krug (Würzburg) wrapping LibSVM Support-Vector-Machine (Chang & Lin 2011), Maximum Entropy (Nigam et al. 1999) and Naïve Bayes (John & Langley 1995) and implemented in MALLET (McCallum 2002). Random Forest (Breiman 2001) and JRip (Cohen 1995) were applied using Weka. All experiments were validated using 10-fold cross-validation unless otherwise stated.

Error analysis

The machine learning algorithms' incorrect assignments on the gold standard (false positives and false negatives) were manually analyzed in order to detect the errors' underlying causes.

Automatic tagging of unseen texts

Using the best-performing model, all sentences in the text collection were tagged for containing direct speech or not. The distribution of ratios of direct speech / non-direct speech was calculated for the three subgenres and five decades covered by the collection. Performance on these unseen texts was checked manually on a random sample. (We sampled 2300 sentences, i.e. 100 random sentences each from a sample of 23 novels stratified by ratio of direct speech.)

Results and Discussion

Recognition of direct speech

Table 1 depicts the performance for different conditions.

	Direct speech (3222 Instances)			Non-direct speech (2512 Instances)			Weighted average (5734 instances)			Without Speechsign
	Precision	Recall	F1 Score	Precision	Recall	F1 Score	Precision	Recall	F1 Score	F1 Score
Baseline Speechsign	0.948	0.569	0.711	0.634	0.96	0.764	0.810	0.740	0.734	
N.Bayes	0.863	0.906	0.884	0.834	0.884	0.859	0.850	0.896	0.873	0.831
MaxEnt	0.894	0.887	0.89	0.856	0.865	0.861	0.877	0.877	0.877	0.847
JRip	0.881	0.912	0.896	0.882	0.842	0.861	0.881	0.881	0.881	0.849
LibSVM	0.899	0.902	0.9	0.873	0.87	0.871	0.888	0.888	0.887	0.859
Random-Forest	0.939	0.925	0.932	0.942	0.953	0.948	**0.940**	**0.937**	**0.939** *	**0.924**

Table 1: Performance (10-fold cross-validation on the gold standard)

Our baseline is using the speech sign (i.e. the long hyphen) as the only feature, which yields an F1 score of 0.734. Random-Forest performs best, with an F1 score of 0.939, which we consider to be an impressive result. Even when excluding the speech sign from the features, we still reach an F1 score of 0.924, much better than the hyphen alone.

After inspecting the models, it becomes clear that only very few features carry strong cues for direct speech, namely (and unsurprisingly) the initial long hyphen. Most other features, taken separately, carry weak signals in either direction, but become relevant in combination.

Error analysis reveals that incorrect assignments (false positives and negatives) are frequently due to imperfect sentence segmentation. Several features which have been previously used to define and recognize direct speech (question / exclamation marks, interjections, verbal tenses) also cause incorrect assignments, especially in the context of homodiegetic narration, where the narrator is somewhat involved in the plot so that his narrator speech is similar to direct speech. Finally, letters are sometimes mistaken for direct speech, which makes sense given that in most of them, one person addresses one or several other people.

Distribution of direct speech in the corpus

We applied the best-performing algorithm (Random Forest) to the entire text collection. Evaluation shows a certain drop in performance, with a weighted average success rate of 0.844, indicating less-than-perfect generalization. We noted a welcome absence of any strong bias for either direct or non-direct speech. Our results suggest that the average proportion of direct to non-direct speech across the collection is 61% sentences with direct speech (and 39% without direct speech).

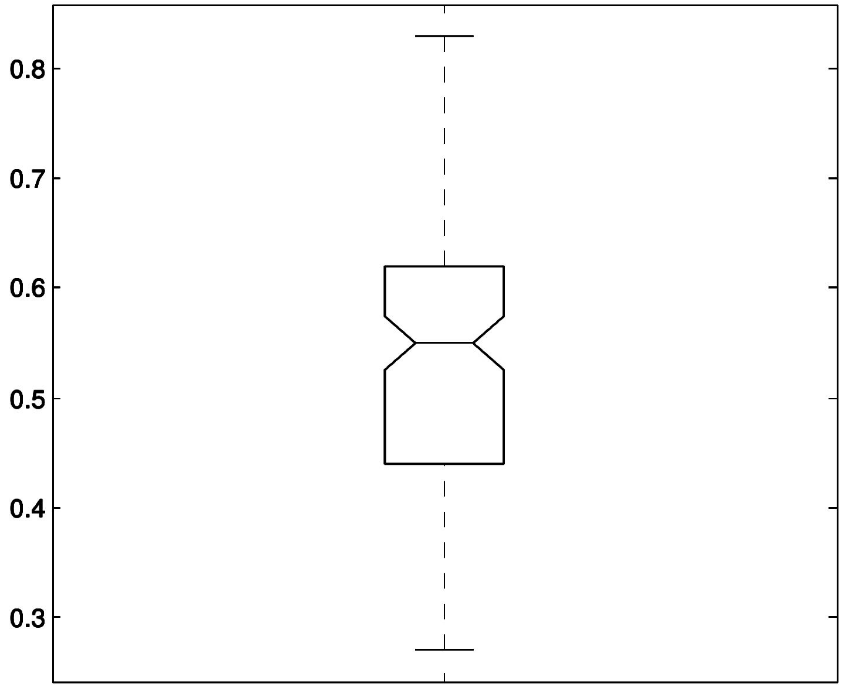


Figure 3: Ratio of direct to non-direct speech in 127 novels.

While variance is considerable (see figure 3), the proportion of direct speech in French nineteenth-century novels is overall much higher than expected (and higher, for example, than the 35% reported by Brunner 2015 for German novellas).

Figure 4 shows that both fantastic novels and crime fiction have a significantly higher median for proportion of direct-speech than 'littérature blanche', but do not differ significantly from each other (for significance tests, we used the non-parametric Kruskal-Wallis test at a significance level of 1%).

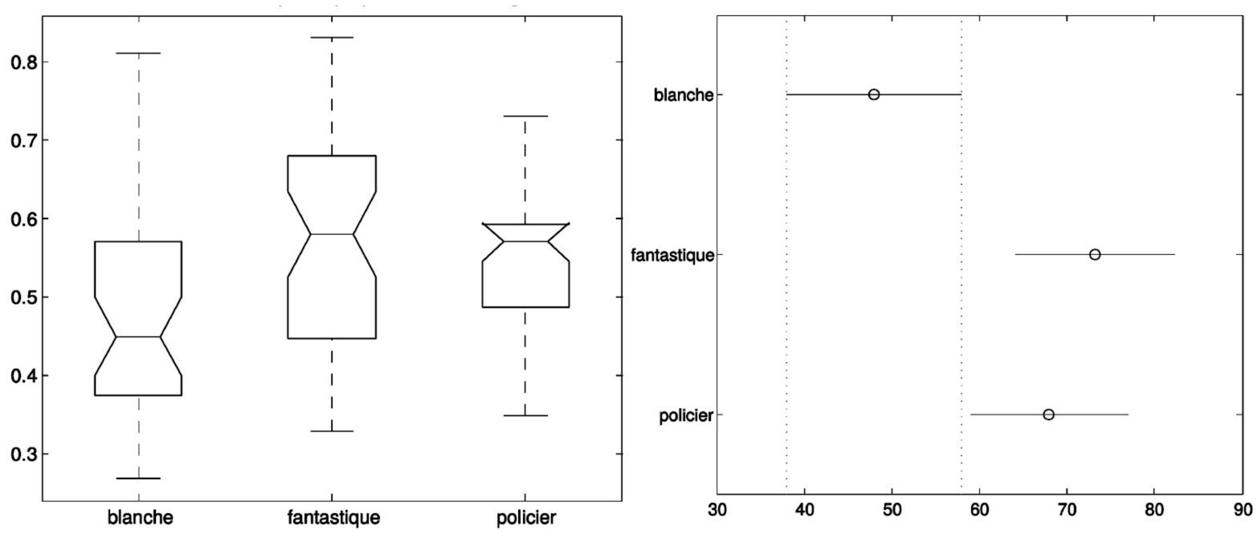


Figure 4: Distribution (left) and significance (right)
of direct to non-direct speech ratios across three subgenres

Figure 5 shows that only the ratios for the 1850s and the 1880s have a significantly differing level. However, because the decades do not have perfectly balanced subgenre proportions, this is probably due to a subgenre imbalance rather than an effect of the time period.

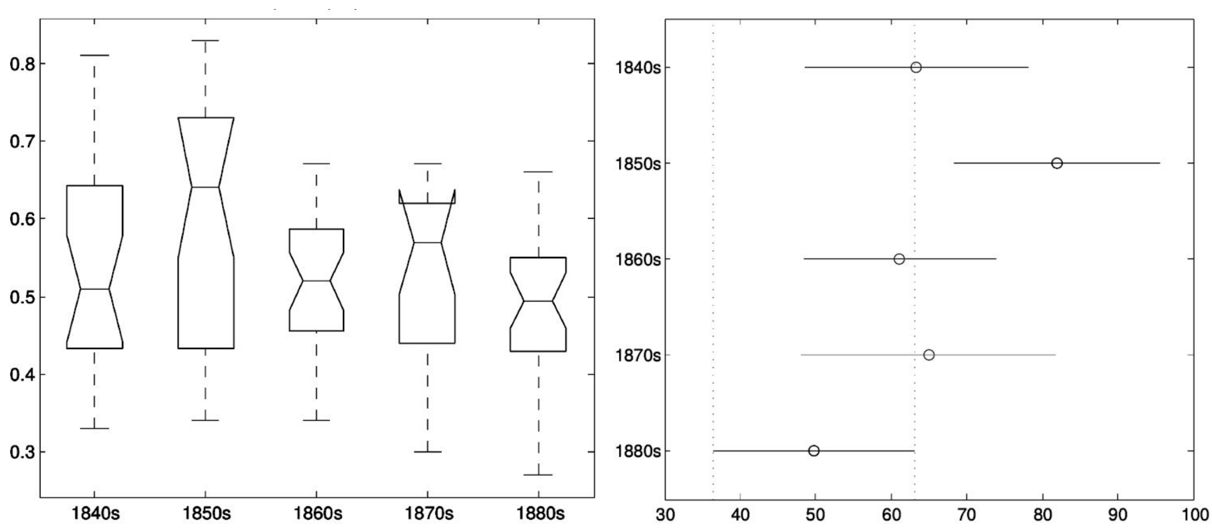


Figure 5: Distribution (left) and significance (right) of direct to non-direct speech ratios across five decades

Conclusions and Future Work

Using a wide range of linguistic markers allows the reliable identification of direct speech, even in the absence of clear typographic markers. Performance is excellent to good (F1-score of 0.94 on the gold standard, weighted average success rate of 0.844 on unseen texts). Using our method reveals that nineteenth-century French novels contain a large proportion of sentences with direct speech (61% on average). Also, there are previously unseen differences in direct speech proportion for subgenre, but not for time period.

For future work, we plan to use several strategies to improve performance. One is to add more sequential information to our set of features. Examples include the position, inside a sentence, of certain lexical or typographical features as well as linguistic cues preceding and following direct speech. Also, we plan to expand our corpus to make it more balanced in terms of genres and decades. This will allow us to discover genre-related patterns of interest to literary historians in a more reliable manner and assess their significance with more confidence.

Supplementary material

Supplementary material can be found at: https://github.com/cligs/projects/tree/master/2016/dh.

References

Allison

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Annex 1: Features used

List of features used, sorted by descending rank by a one-rule classifier.

average merit	average rank	attribute
74.028 +- 0.168	1 +- 0	79 SPEECHSIGN
71.743 +- 0.16	2 +- 0	57 VER:impf
65.847 +- 0.234	3 +- 0	54 VER:pres
63.893 +- 0.155	4 +- 0	55 VER:simp
63.248 +- 0.136	5 +- 0	6 PUNCMARKDOT
59.48 +- 0.12	6 +- 0	29 MATCHINGPPER_SON
58.835 +- 0.094	7.7 +- 0.64	30 MATCHINGPPER_SES
58.695 +- 0.208	8.1 +- 0.94	24 MATCHINGPPER_IL
58.713 +- 0.104	8.4 +- 0.92	35 VERB_MOTION
58.364 +- 0.083	10.6 +- 0.49	28 MATCHINGPPER_SA
58.344 +- 0.417	10.8 +- 1.78	7 SENTENCELENGTH
58.172 +- 0.078	11.7 +- 0.46	61 VER:subi
57.492 +- 0.091	14 +- 1.41	25 MATCHINGPPER_ELLE
57.422 +- 0.103	14.5 +- 1.36	44 VERB_PERCEPTION
57.387 +- 0.248	14.9 +- 1.51	50 INNERSUBCLAUSE

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57.356 +- 0.4        15.8 +- 2.09   48 UNKNOWNLEMMA
57.213 +- 0.07       16.5 +- 1.02   31 MATCHINGPPER_LEUR
57.143 +- 0.162      17.3 +- 1.1    60 VER:ppre
56.672 +- 0.042      20.2 +- 0.98   36 VERB_BODY
56.672 +- 0.115      21   +- 1.84   52 VER:cond
56.62  +- 0.136      21.7 +- 2.1    40 VERB_EMOTION
56.567 +- 0.072      22.3 +- 1.19   26 MATCHINGPPER_ILS
56.497 +- 0.033      23.9 +- 1.3    41 VERB_COGNITION
56.428 +- 0.044      25   +- 1      46 VERB_CONSUMPTION
56.201 +- 0.005      34.5 +- 4.06   20 MATCHINGPPER_VOTRE
56.339 +- 0.176      35.4 +-18.69   32 COMMAS
56.201 +- 0.005      35.8 +- 4.19   21 MATCHINGPPER_VOS
56.201 +- 0.005      35.8 +- 6.4    22 MATCHINGPPER_TOI
56.201 +- 0.005      36.3 +- 4.2    17 MATCHINGPPER_TES
56.201 +- 0.005      37.6 +- 7.35    5 PUNCMARKCOLON
56.195 +- 0.018      37.7 +-13.33   18 MATCHINGPPER_NOTRE
56.201 +- 0.005      38.2 +- 3.16   23 MATCHINGPPER_MOI
56.424 +- 0.296      38.4 +-25.85   47 VERB_COMMUNICATION
56.201 +- 0.005      38.6 +- 6.45    4 PUNCMARKEXCL
56.201 +- 0.005      38.7 +- 3.44   16 MATCHINGPPER_TON
56.201 +- 0.005      39.4 +- 4.82   15 MATCHINGPPER_TA
56.201 +- 0.005      39.6 +- 6.45    3 PUNCMARKQUSTION
56.201 +- 0.005      40.2 +- 8.81    8 MATCHINGPPER_JE
56.201 +- 0.005      41.8 +-10.17    9 MATCHINGPPER_TU
56.201 +- 0.005      43.5 +- 9.19   10 MATCHINGPPER_NOUS
56.201 +- 0.005      43.5 +- 2.84   13 MATCHINGPPER_MON
56.201 +- 0.005      44.6 +- 4.43   12 MATCHINGPPER_MA
56.201 +- 0.005      44.7 +- 6.47   11 MATCHINGPPER_VOUS
56.261 +- 0.436      45.6 +-27.28    1 AmmountOfPPER
56.201 +- 0.005      45.8 +- 9.65   75 INTERJECTION_FI
56.201 +- 0.005      48   +-14.72   76 INTERJECTION_HEP
56.201 +- 0.005      50.2 +- 9.34   73 INTERJECTION_EH
56.201 +- 0.005      50.2 +- 6.27   74 INTERJECTION_EUH
56.201 +- 0.005      51.3 +- 3.66   81 INTERJECTION_MADAME
56.203 +- 0.08       51.3 +-23.56   37 VERB_COMPETITION
56.201 +- 0.005      52.1 +-15.75   58 VER:infi
56.201 +- 0.005      52.3 +-16.54   56 VER:futu
56.201 +- 0.005      53   +- 8.91   78 INTERJECTION_OUSTE
56.201 +- 0.005      54.7 +-17.43   34 VERB_CONTACT
56.162 +- 0.116      55.6 +-18.7    33 VERB_WEATHER
56.201 +- 0.005      56.9 +- 6.55   64 INTERJECTION_OH
56.201 +- 0.005      57.3 +- 4.5    63 INTERJECTION_AH
56.135 +- 0.087      58   +-24.31   19 MATCHINGPPER_NOS
56.193 +- 0.015      58.7 +-13.46   77 INTERJECTION_OUF
56.201 +- 0.005      59.3 +- 9.42   67 INTERJECTION_HÉLAS
56.143 +- 0.07       59.6 +-16.69   14 MATCHINGPPER_MES
56.201 +- 0.005      59.9 +- 4.5    42 VERB_STATIVE
56.201 +- 0.005      60.2 +- 2.64   62 VER:subp
56.201 +- 0.005      60.6 +- 8.39   71 INTERJECTION_CHUT
56.201 +- 0.005      62   +- 6.36   70 INTERJECTION_HEM
56.193 +- 0.015      62.5 +-10.87   66 INTERJECTION_HEIN
56.197 +- 0.011      62.6 +- 8      65 INTERJECTION_HÉ
56.201 +- 0.005      62.7 +- 5.87   51 DEIKTIKA
56.201 +- 0.005      63   +- 4.07   80 INTERJECTION_MONSIEUR
56.201 +- 0.005      63   +-11.79   53 VER:impe
56.005 +- 0.298      63.8 +-24.78   38 VERB_POSSESSION
56.201 +- 0.005      64   +- 5.67   39 VERB_SOCIAL
56.201 +- 0.005      64.3 +- 4.86   45 VERB_CHANGE
56.197 +- 0.013      64.7 +- 8.74   68 INTERJECTION_BAH
56.201 +- 0.005      64.7 +- 5.27   59 VER:pper
56.197 +- 0.015      65.2 +- 7.08   69 INTERJECTION_HOLÀ
56.139 +- 0.062      66.7 +-20.16   27 MATCHINGPPER_ELLES
56.183 +- 0.008      71.8 +- 5.23   72 INTERJECTION_BRAVO
56.005 +- 0.121      74.2 +- 9.41   43 VERB_CREATION
56.079 +- 0.038      77.4 +- 1.56    2 AmmountOfDET
55.99  +- 0.142      78.1 +- 3.73   49 POSNPP
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Annex 2: Text collection

author-name	**title**	**year**	**subgenre**	**narration**
Balzac	Pierrette	1840	blanche	heterodiegetic
Balzac	TenebreuseAffaire	1841	policier	heterodiegetic
Balzac	AlbertSavarus	1842	blanche	heterodiegetic

Sue	MysteresParis02	1842	fantastique	heterodiegetic
Sue	MorneDiable	1842	fantastique	heterodiegetic
Sue	MysteresParis01	1842	fantastique	heterodiegetic
FevalPP	LoupBlanc	1843	blanche	heterodiegetic
Dumas	Eppstein	1843	fantastique	heterodiegetic
FevalPP	MysteresLondres1	1843	policier	heterodiegetic
FevalPP	FanfaronsRoi	1843	blanche	heterodiegetic
FevalPP	MysteresLondres3	1843	policier	heterodiegetic
Sue	MysteresParis04	1843	fantastique	heterodiegetic
Sue	MysteresParis05	1843	fantastique	heterodiegetic
Sue	JuifErrant	1844	fantastique	heterodiegetic
Sand	PecheAntoine	1845	blanche	heterodiegetic
Sue	PaulaMonti	1845	fantastique	heterodiegetic
FevalPP	Quittance2Galerie	1846	blanche	heterodiegetic
Sand	LucreziaFloriani	1846	blanche	homodiegetic
Balzac	CousineBette	1846	blanche	heterodiegetic
Gautier	PartieCarrée	1848	fantastique	heterodiegetic
Sue	MysteresPeuple02	1849	fantastique	heterodiegetic
Dumas	Fantômes	1849	fantastique	homodiegetic
Dumas	Olifus	1849	fantastique	homodiegetic
Dumas	ColliersVelours	1850	fantastique	heterodiegetic
Sue	MysteresPeuple03	1850	fantastique	heterodiegetic
Sue	MysteresPeuple04	1850	fantastique	heterodiegetic
Sue	MysteresPeuple07	1851	fantastique	heterodiegetic
Sue	MysteresPeuple06	1851	fantastique	heterodiegetic
Aurevilly	Ensorcelée	1852	fantastique	homodiegetic
Ponson	Baronne	1852	fantastique	heterodiegetic
FevalPP	ReineEpees	1852	blanche	heterodiegetic
Ponson	FemmeImmortelle	1852	fantastique	heterodiegetic
Sue	MysteresPeuple09	1853	fantastique	heterodiegetic
Sue	MysteresPeuple08	1853	fantastique	heterodiegetic
Sue	MysteresPeuple11	1854	fantastique	heterodiegetic
Sue	MysteresPeuple10	1854	fantastique	heterodiegetic
Sue	MysteresPeuple12	1855	fantastique	heterodiegetic
FevalPP	MadameGilBlas	1856	blanche	homodiegetic
Gautier	Avatar	1856	fantastique	heterodiegetic
FevalPP	Louve2	1856	blanche	heterodiegetic
Sue	MysteresPeuple13	1856	fantastique	heterodiegetic
Gautier	RomanMomie	1857	fantastique	heterodiegetic
Sue	MysteresPeuple16	1857	fantastique	heterodiegetic
Dumas	MeneurLoups	1857	fantastique	heterodiegetic
Sue	MysteresPeuple15	1857	fantastique	heterodiegetic
Ponson	ClubValets2	1858	policier	heterodiegetic
Ponson	ExploitsRocambole3	1859	policier	heterodiegetic
Ponson	ExploitsRocambole2	1859	policier	heterodiegetic
Ponson	ExploitsRocambole1	1859	policier	heterodiegetic
Sand	ElleLui	1859	blanche	heterodiegetic
Ponson	Chevaliers	1860	policier	heterodiegetic
Féval	Ténèbre	1860	fantastique	heterodiegetic
FevalPP	ChevalierTenebre	1861	fantastique	homodiegetic
Aimard	RodeursFrontieres	1861	blanche	heterodiegetic
Hugo	Miserables1Fantine	1862	blanche	heterodiegetic
Ponson	TestamentGrainDeSel	1862	policier	heterodiegetic
About	OreilleCassée	1862	fantastique	heterodiegetic
Villiers	Isis	1862	fantastique	heterodiegetic
FevalPP	HabitsNoirs1	1863	policier	heterodiegetic
Aurevilly	PrêtreMarié	1864	fantastique	homodiegetic
Féval	Vampire	1865	fantastique	homodiegetic
Gaboriau	Lerouge	1865	policier	heterodiegetic
FevalPP	HabitsNoirs2Coeur	1865	policier	heterodiegetic
Ponson	Breda	1866	fantastique	heterodiegetic
Ponson	ResurrectionRocambole2	1866	policier	heterodiegetic
Verne	CapitaineHatteras	1866	blanche	heterodiegetic
Ponson	DernierMot3	1867	policier	heterodiegetic
Ponson	DernierMot4	1867	policier	heterodiegetic
Gaboriau	EsclavesParis2	1867	policier	heterodiegetic
Ponson	DernierMot2	1867	policier	heterodiegetic
Ponson	MiseresLondres3	1868	policier	heterodiegetic
Aimard	Ourson	1868	blanche	heterodiegetic
Ponson	MiseresLondres2	1868	policier	heterodiegetic
Ponson	MiseresLondres4	1868	policier	heterodiegetic
FevalPP	HabitsNoirs3Rue	1868	policier	heterodiegetic
Ponson	FéeAuteuil	1868	fantastique	heterodiegetic
Flaubert	Education	1869	blanche	heterodiegetic

FevalPP	HabitsNoirs4Arme	1869	policier	heterodiegetic
FevalPP	HabitsNoirs5Maman	1869	policier	heterodiegetic
Gouraud	EnfantsFerme	1869	blanche	heterodiegetic
Gaboriau	MonsieurLecoq2	1869	policier	heterodiegetic
Zola	FortuneRougon	1870	blanche	heterodiegetic
Ponson	CordePendu1	1870	policier	heterodiegetic
Ponson	CordePendu2	1870	policier	heterodiegetic
Gaboriau	VieInfernale2	1870	policier	heterodiegetic
Gaboriau	Degringolade1	1872	policier	heterodiegetic
Gaboriau	Degringolade3	1872	policier	heterodiegetic
Gaboriau	Degringolade2	1872	policier	heterodiegetic
Gaboriau	CordeCou2	1873	policier	heterodiegetic
Zola	VentreParis	1873	blanche	heterodiegetic
Gaboriau	CordeCou1	1873	policier	heterodiegetic
Gaboriau	Argent1	1874	policier	heterodiegetic
Gaboriau	Argent2	1874	policier	heterodiegetic
FevalPP	VilleVampire	1875	fantastique	homodiegetic
Zola	AbbeMouret	1875	blanche	heterodiegetic
Verne	HectorServadac	1877	fantastique	heterodiegetic
Malot	Cara	1878	blanche	heterodiegetic
AimardAuriac	AigleNoirDacotahs	1878	blanche	heterodiegetic
Stolz	SecretLaurent	1878	blanche	heterodiegetic
FevalPP	HommeSansBras	1881	policier	heterodiegetic
Loti	RomanSpahi	1881	blanche	heterodiegetic
Boisgobey	Omnibus	1881	policier	heterodiegetic
Gaboriau	AmoursEmpoisonneuse	1881	policier	heterodiegetic
Stolz	Mesaventures	1881	blanche	heterodiegetic
FevalPP	HistoireRevenants	1881	fantastique	heterodiegetic
Gouraud	ChezGrandMere	1882	blanche	heterodiegetic
Aurevilly	HistoireSans	1882	fantastique	heterodiegetic
Maupassant	UneVie	1883	blanche	heterodiegetic
Rachilde	MVénus	1884	fantastique	heterodiegetic
Boisgobey	Voilette	1885	policier	heterodiegetic
Zola	Germinal	1885	blanche	heterodiegetic
Ohnet	GrandeMarnière	1885	blanche	heterodiegetic
Zola	Oeuvre	1886	blanche	heterodiegetic
Villiers	EveFuture	1886	fantastique	heterodiegetic
Boisgobey	RubisOngle	1886	policier	heterodiegetic
Malot	Zyte	1886	blanche	heterodiegetic
Loti	PecheurIslande	1886	blanche	heterodiegetic
Mary	RogerLaHonte	1886	blanche	heterodiegetic
Malot	Conscience	1888	blanche	heterodiegetic
Boisgobey	OeilChat1	1888	policier	heterodiegetic
Boisgobey	Chat2	1888	policier	heterodiegetic
Gouraud	QuandGrande	1888	blanche	heterodiegetic
Boisgobey	MainFroide	1889	blanche	heterodiegetic
Boisgobey	Opera2	1889	policier	heterodiegetic
Boisgobey	MainFroide	1889	policier	heterodiegetic
Boisgobey	Opera1	1889	policier	heterodiegetic
Boisgobey	DoubleBlanc	1889	policier	heterodiegetic