

Article

Identification of judicial outcomes in judgements: A Generalized Gini-PLS approach

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² 1. Introduction

³ **Judicial prediction** is the ability to predict what a judge will decide on a given case. Is it possible
⁴ to develop efficient predictive models to automatize such predictions? This question has long been
⁵ driving several initiatives at the crossroads of Artificial Intelligence and Law; in particular through
⁶ the development of predictive models based on the alignment of computable features of the case that
⁷ were available to the judge prior to the judgment, with computable features of the judge's decision on
⁸ the case. In this line of works, this paper presents a study towards the development of such **predictive**
⁹ **models** taking advantage of Machine Learning and Natural Language Processing techniques. The
¹⁰ legal vocabulary being notoriously ambiguous, we first detail important concepts that will be used
¹¹ thereafter.

ce n'est pas forcément avéré

¹² A *case* begins with a complaint requesting **remedy against the wrongful doing of the defendant**.
¹³ The features of the case are the circumstances existing prior to the filing of the complaint, that is a set
¹⁴ of facts sufficient to justify a right to file a complaint.

¹⁵ A *claim* is a the request made by a plaintiff against a defendant, seeking legal remedy. Claims can
¹⁶ be grouped into different categories, depending on the rule applicable and the type of remedy sought
¹⁷ (e.g. injunctive relief, cease and desist order, damages).

¹⁸ A *judgment* summarizes the different rulings made by a judge about a certain case into a document.
¹⁹ Judgments therefore contains many features that can be extracted (e.g., type of court, name of the
²⁰ parties, claims made by the parties, judge's decisions on the claims). A complaint is a judgement that
²¹ can contain many different claims, seeking different types of remedy. Therefore, in general, a judgment
²² concern different types of claims.

²³ The *decision* is a ruling made on a particular claim. We further consider that the judge's decision
²⁴ on a claim is either accepted or rejected. Note that a judgment must be distinguished from the judge's
²⁵ decision on a specific claim.

²⁶ As we stressed, claims can be grouped into specific categories depending on their nature, e.g.
²⁷ several claims may refer to the notion of "child care"; such categories are defined *a priori* by jurists
²⁸ for the analysis of a corpus of judgments of interest. **In addition, a judgment most of the time only**
²⁹ **contains a single claim of a given category.**¹ In this context, we are interested in the definition of

Il faudrait bien préciser que nous l'avons observé dans le jeu de données que nous avons annoté

¹ A corpus description and a descriptive analysis is provided in the next section.

classification models able to identify
 30 predictive models able to predict the judge's decision expressed in a judgment for a specific category
 31 of claims. Otherwise stated, knowing that a judgment contains a single claim of a given category, the
 32 model will have to answer the following question analysing the judgment (textual document): has the
 33 claim been accepted or rejected? Developing efficient predictors of the outcome of specific categories
 34 of claims is of major interest for the analysis of large corpus of judgments. It for instance paves the
 35 way for large statistical analysis of correlations between aspects of the case (e.g. parties, location of
 36 the court) and outcomes for specific categories of claims. Such analyses are important for theoretical
 37 studies on law enforcement and future development of models able to predict the outcome of cases.²

given the hypothesis
that ...
confusion possible :
nous disons que nous
faisons de la prédiction
qui sera la base de la
prédiction

38 These last years, the methodology of judicial predictions were mostly exclusively based on the
 39 employ of neural networks, which may be seen as the most flexible models for classification and
 40 predictions of legal decisions. [2] use a Bi-LSTM network running on words on a task of extracting
 41 contractual clauses. [3] have shown the superiority of convolutional networks over Suport Vector
 42 Machines for the classification of texts. The use of a Bi-GRU has become a standard approach, see [4].
 43 Performance of 92% was obtained on the identification of criminal charges and on judicial outcomes
 44 from Chinese criminal decisions ([5]). This type of approach can be used successfully on judgements
 45 in civil matters ([6]). Bi-LSTM networks coupled with a representation of the judgement in the form
 46 of a tensor achieve performance around 93% on a corpus of 1.8 million Chinese criminal judgments
 47 ([7]). This work has been successfully replicated on a body of judgments of the European Court of
 48 Human Rights in English, with F-measure performance of 80% for bi-GRU networks with attention,
 49 and Hierarchical BERT ([8]). On the same corpus, the development of a specific lexical embedding
 50 ECHR2Vec makes it possible to reach performances around 86% ([9]). Similar performances of 79%
 51 are obtained by TF-IDF (Term Frequency - Inverse Document Frequency) in the Portuguese language
 52 ([10]). Although neural networks enable very good performances to be achieved, we defend in this
 53 paper the use of compression machine learning models based on word representations à la TF-IDF
 54 with different variants corresponding to different weighting schemes.

55 The methodology of judicial predictions therefore depends on the ability of a model to predict the
 56 judge's decision on a claim inherent to a given category - without knowing the precise localization
 57 of the statement of the judge's decision inside a judgment. In this context, extracting the result of
 58 a claim can be formulated as a task of binary text classification. To tackle this task, we consider in
 59 this paper the supervised machine learning paradigm assuming that a set of annotated judgments,
 60 i.e. labelled dataset, is provided for each category of claims of interest. We therefore aim to use
 61 the labelled dataset for training an algorithm to recognize whether the request has been rejected or
 62 accepted. Considering this setting, the paper presents various models and empirically compares them
 63 on a corpus of French judgments. A statistical analysis of the impact of various technical aspects
 64 generally involved in the classification of texts which consists of a combination of representations of
 65 judgments and classification algorithms is proposed. This analysis sheds light on certain configurations
 66 making it possible to determine judges' decisions of a claim. We also propose the generalized Gini-PLS
 67 algorithm which is an extension of the simple Gini-PLS model [11]. This generalized Gini-PLS consists
 68 in adding a regularization parameter that makes it possible to better adapt the regression with respect
 69 to the information in the distribution tails while attenuating, as in the simple Gini-PLS, the influence
 70 exerted by outliers. We also propose a new regression (LOGIT-Gini-PLS) which is better suited to the
 71 explanation of a target variable when the latter is a binary variable. These two models have never been
 72 applied to text classification.

² Note that traditional text classification techniques obtain good performance predicting if a judgment contains a claim of a specific category, see [1]. Obtaining relevant statistics about judge's decisions on a given category of claim would therefore be based on (i) applying aforementioned model to distinguish judgments containing a claim of the category of interest, and (ii) applying the type of models studied in this paper to know the outcome of previously identified judgments.

⁷³ The paper is organized as follows: Section 2 presents characteristics of the corpus used for this
⁷⁴ study and motivates the modelling of the task adopted in this paper (i.e. decision outcome prediction
⁷⁵ as a binary text classification). Section 3 presents the different TF-IDF vectorizations of the judgments.
⁷⁶ Section 4 presents the proposed generalized (LOGIT) Gini-PLS algorithms for text classification. Section
⁷⁷ 5 presents our experiments and results. Section 6 concludes our study.

⁷⁸ 2. Datasets and modelling motivations

⁷⁹ We assume in this paper that predicting judge's decisions may be studied through the lens of the
⁸⁰ definition of binary text classification models. This positioning is based on discussions with jurists and
⁸¹ motivated by analyses performed on labelled datasets of French judgments. Six datasets built from a
⁸² corpus of French judgments are considered in our study, one for each of the six categories of claims
⁸³ introduced in Table 1. A total of 341 judgments have been manually annotated by a jurist.

Dataset	Description	Number of judgments
ACPA	Civil fine for abuse of process	246
CONCDEL	Damages for unfair competition	238
DANAIS	Damages for abuse of process	421
DCPPC	declaration of claim to liabilities of the collective procedure	218
DORIS	damages for neighborhood disturbance	164
STYX	irrecoverable expenditure	123

Table 1. Categories of claims of the study

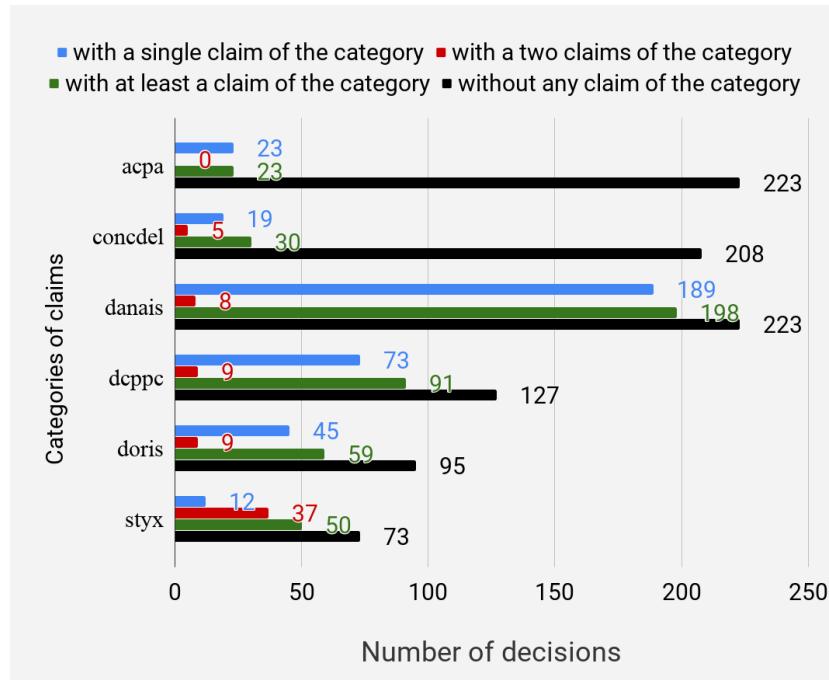
⁸⁴ The semantics of the membership of a judgments into a category is: the judgments contains a
⁸⁵ claim of that category, i.e. all the judgments into the ACPA category contain a claim related to Civil
⁸⁶ fine for abuse of process. Table 2 presents parts of a judgment of that category [ACPA]. The parts refer
⁸⁷ to the mentions of the claim and to corresponding decision respectively. Figure 1 presents additional
⁸⁸ details about the datasets.

	In French	In English
claim	À l'audience, la SA SFP reprenant oralement ses conclusions visées par le greffier, demande à la cour de: - confirmer le jugement déféré - débouter M. S. de l'ensemble de ses demandes - le condamner à payer une amende civile de 1.500 pour procédure abusive en application de l'article 32-1 du code de procédure civile - le condamner à payer la somme...	At the hearing, SA SFP orally resuming its conclusions referred to in the clerk, requests the court to: - confirm the judgment referred - dismiss Mr S. of all his requests - order him to pay a civil fine of 1,500 for abusive procedure in application of article 32-1 of the code of civil procedure - order him to pay the sum ...
decision	PAR CES MOTIFS LA COUR, CONFIRME le jugement déféré en toutes ses dispositions; Y ajoutant, DIT n'y avoir lieu à application des dispositions de l'article 700 du code de procédure civile; REJETTE le surplus des demandes ; CONDAMNE M Khellil S. aux dépens d'appel.	FOR THESE REASONS THE COURTYARD, CONFIRMS the judgment referred in all its provisions; Adding to it, SAID to take place there in application of the provisions of article 700 of the code of Civil Procedure; REJECTS excess requests; ORDERS M Khellil S. at costs of appeal.

Table 2. Extract from "Cour d'appel, Paris, Pôle 6, chambre 9, 18 Mai 2016 – n14/11380"

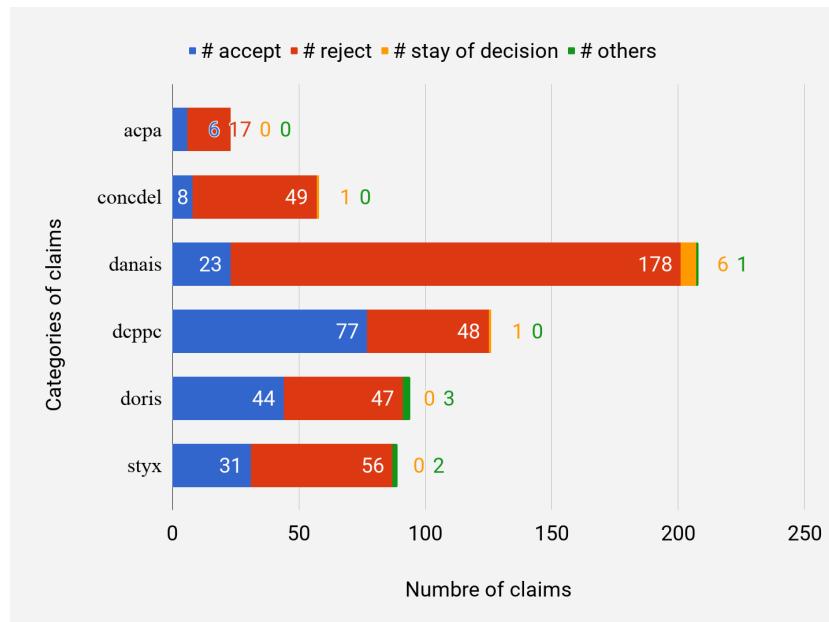
⁸⁹ **Observation 1.** *Decisions most often only contain a single claim of a specific category.*

⁹⁰ On the one hand, the statistics on the labelled data show that the judgments contain for the most
⁹¹ part a single claim of a category. The percentage of judgments having only one request of a category is
⁹² respectively: 100% for ACPA, 63.33% for CONCDEL, 95.45% for DANAIS, 80.22% for DCPPC, and
⁹³ 76.21% for DORIS. However, we note the exception of the STYX category (damages on article 700

**Figure 1.** Number of claims in judgments

94 CPC), where in most of the judgments, there are rather 2 claims. This exception can be justified by the
 95 fact that each party generally makes this type of request because it relates to the reimbursement of
 96 legal costs.

97 On the other hand, it exists few judgements with two or more claims. In this case, the classification
 98 task of any claim becomes difficult since specific vocabulary and sentences may appear in the
 99 judgement related to other claims (although there are in the same category). This may be embodied by
 100 noise or outliers in the dataset of each claim category. The use of Gini estimators is therefore welcome
 101 to handle outlying observations.

**Figure 2.** Distribution of judges' decisions within each category of claims

¹⁰² **Observation 2.** *The judge's decisions are binary: accept or reject.*

¹⁰³ Figure 2 highlights the fact that outcomes of a given claim are most often accepted or rejected,
¹⁰⁴ and that other forms of results are very rare.

¹⁰⁵ Theses observations motivate the interest of developing binary classifier for predicting the
¹⁰⁶ outcome of a claim appertaining to a specific category.

¹⁰⁷ **Observation 3.** *The algorithm must be able to deal with the important number of tokens of judgments.*

¹⁰⁸ Figure 3 illustrates the distribution of the judgments lengths (number of tokens, i.e. words).
¹⁰⁹ We note that the texts are long in comparison to those usually considered by state-of-the-art text
¹¹⁰ classification approaches. As we will discuss later, this particularity will hamper the use of some
¹¹¹ efficient existing approaches such as PLS algorithms for compression.

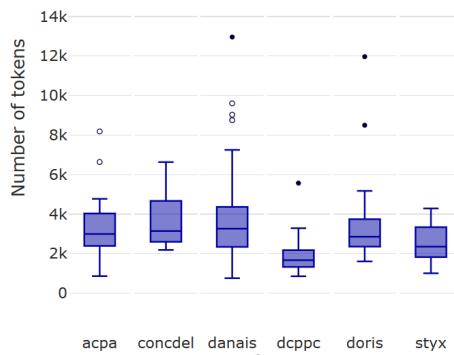


Figure 3. Distribution of the size of the decision by tokens

¹¹² **Observation 4.** *In some claim categories, there may exist strong imbalance between the outcomes accept/reject.*

¹¹³ Table 3 presents the final statistics of the dataset used for both training and evaluating the
¹¹⁴ predictive models evaluated in this study. As can be seen, 4 claim categories out of 6 exhibit strong
¹¹⁵ unbalanced decisions.

Dataset	Accepted	Rejected	Total
ACPA	6 (26.09%)	17 (73.91%)	23
CONCDEL	4 (22.22%)	14 (77.78%)	18
DANAIS	21 (11.23%)	166 (88.77%)	187
DCPPC	48 (66.66%)	24 (33.33%)	72
DORIS	23 (52.27%)	21 (47.72%)	44
STYX	4 (33.33%)	8 (66.67%)	12

Table 3. Class distributions per claim category

¹¹⁶ 3. Texts classification

¹¹⁷ Text classification allows judgments to be organized in predefined groups. This technique has
¹¹⁸ received a large audience for a long time. Two technical choices mainly influence the performance of
¹¹⁹ the classification: the representation of the texts and the choice of the classification algorithm. In the
¹²⁰ following, the predicted variable is denoted y , the predictors are denoted x , the learning base including
¹²¹ the observations of the sample is expressed as $D = \{(x_i, y_i)_{i=1 \dots N}\}$, and C represents claim categories.

Considering a vocabulary $V = \{t_1, t_2, \dots, t_n\}$, we further assume that every judgment $d \in D$ is represented as a TF-IDF vector embedding (*Term Frequency - Inverse Document Frequency*) [22] $\vec{d} \in \mathbb{R}^n$, where each dimension $1 \leq k \leq n$ refers to word $t_k \in V$ and $\vec{d}[k] = w(t_k, d)$ is the weight of t_k in d

Notation	Description
t	a term
d	a judgement (document)
$ d $	size of d (number of tokens)
c	a label
\bar{c}	the other labels
D	the global set of documents ($N = D $)
D_c	the set of documents labeled with c
$D_{\bar{c}}$	the set of documents not labeled with c
N_t	the number of documents containing t
$N_{\bar{t}}$	the number of documents without t
$N_{t,c}$	the number of documents of c with t
$N_{\bar{t},c}$	the number of documents of c without t
$N_{t,\bar{c}}$	the number of documents of \bar{c} with t
$N_{\bar{t},\bar{c}}$	the number of documents of \bar{c} without t
$DF_{t c}$	proportion of documents of c with t ($DF_{t c} = \frac{N_{t,c}}{ D_c }$)
$DF_{c t}$	proportion of documents of c in the global set of documents with t

Table 4. Notation used in formulas.

Description	Formula
Inverse document frequency (IDF) [12]	$idf(t) = \log_2 \left(\frac{N}{N_t} \right)$
Probabilistic IDF [13]	$pidf(t) = \log_2 \left(\frac{N}{N_t} - 1 \right)$
BM25 IDF [14]	$bldf(t) = \log_2 \left(\frac{N_t + 0.5}{N_t + 0.5} \right)$
Frequency difference	$\Delta_{DF}(t, c) = DF_{t c} - DF_{t \bar{c}}$
Information gain [15]	$ig(t, c) =$ $\frac{N_{t,c}}{N} \log_2 \left(\frac{N_{t,c} N}{N_t} \right) + \frac{N_{\bar{t},c}}{N} \log_2 \left(\frac{N_{\bar{t},c} N}{N_t D_c } \right)$ $+ \frac{N_{t,\bar{c}}}{N} \log_2 \left(\frac{N_{t,\bar{c}} N}{N_t D_c } \right) + \frac{N_{\bar{t},\bar{c}}}{N} \log_2 \left(\frac{N_{\bar{t},\bar{c}} N}{N_t D_c } \right)$
Relevance frequency [16]	$rf(t, c) = \log \left(2 + \frac{N_{t,c}}{\max(1, N_{t,\bar{c}})} \right)$
χ^2 coefficient [17]	$\chi^2(t, c) = \frac{N((N_{t,c} N_{\bar{t},\bar{c}}) - (N_{t,\bar{c}} N_{\bar{t},c}))^2}{N_t N_{\bar{t}} D_c D_{\bar{c}} }$
Correlation coefficient [18]	$ngl(t, c) = \frac{\sqrt{N(N_{t,c} N_{\bar{t},\bar{c}}) - (N_{t,\bar{c}} N_{\bar{t},c})}}{\sqrt{N_t N_{\bar{t}} D_c D_{\bar{c}} }}$
GSS coefficient [19]	$gss(t, c) = (N_{t,c} N_{\bar{t},\bar{c}}) - (N_{t,\bar{c}} N_{\bar{t},c})$
Marascuilo coefficient [20]	$mar(t, c) =$ $\frac{\left((N_{t,c} - N_t N_{t,c} / N)^2 + (N_{t,\bar{c}} - N_t D_{\bar{c}} / N)^2 + (N_{\bar{t},c} - D_c N_{\bar{t},c} / N)^2 + (N_{\bar{t},\bar{c}} - N_{\bar{t}} D_{\bar{c}} / N)^2 \right)}{N}$
Smoothed IDF delta [21]	$dsidf(t, c) = \log_2 \left(\frac{ D_{\bar{c}} (N_{t,c} + 0.5)}{ D_c (N_{t,\bar{c}} + 0.5)} \right)$
BM25 IDF delta [21]	$dbldf(t, c) = \log_2 \left(\frac{(D_{\bar{c}} - N_{t,\bar{c}} + 0.5)(N_{t,c} + 0.5)}{(D_c - N_{t,c} + 0.5)(N_{t,\bar{c}} + 0.5)} \right)$

Table 5. Global weighting metrics

defined as the normalized product of a global weight $g(t_k)$ depending on the training corpus and a local weight $l(t_k, d)$ stressing the importance of t_k in judgment d :

$$w(t_k, d) = l(t_k, d) \times g(t_k) \times nf(d)$$

with nf a normalization factor. Table 4 summarizes the notations used in the paper. The global weight is computed following one of the methods presented in Table 5. The local weight is computed from the frequency of occurrences of the word in the judgment using one of the methods of Table 6.

Description	Formula
Gross term statement [22]	$tf(t, d) = \text{Number of occurrences of } t \text{ in } d$
Presence of the word [22]	$tp(t, d) = \begin{cases} 1 & \text{if } tf(t, d) > 0 \\ 0 & \text{otherwise} \end{cases}$
Log Normalization	$logtf(t, d) = 1 + \log(tf(t, d))$
Increased and standardized frequency of the word [22]	$atf(t, d) = k + (1 - k) \frac{tf(t, d)}{\max_{t \in V} tf(t, d)}$
Normalization based on the average frequency of the word [23] (avg is the average)	$logave(t, d) = \frac{1 + \log tf(t, d)}{1 + \log avg_{t \in V} tf(t, d)}$

Table 6. Local weighting metrics

The vector representation of texts generally results in high-dimensional vectors whose coordinates are mostly zero. Consequently, dimension reduction (compression) techniques, such as PLS regressions make it possible to obtain vectors more relevant to classification tasks.

4. Generalized Gini-PLS algorithms for text classification

The Gini-PLS regression has been introduced by [11]. In what follows we propose two Gini-PLS algorithms: a generalized Gini-PLS regression based on the Gini generalized covariance operator, and a combination of the latter to the logistic regression. We first review the PLS algorithm.

4.1. PLS

The advantage of the Gini-PLS algorithm is to reduce the sensitivity to outliers. It is an extension of the PLS analysis (*partial least square*) [24]. The PLS analysis explains the dependence between one or more predicted variables y and predictors $\mathbf{x} = (x_1, x_2, \dots, x_m)$. It mainly consists in transforming the predictors into a reduced number of h orthogonal principal components t_1, \dots, t_h . It is therefore a method of dimension reduction in the same way as the principal component analysis (PCA), the linear discriminant analysis (LDA), and the quadratic discriminant analysis (QDA). The components t_1, \dots, t_h are built in different steps by applying the PLS algorithm repeatedly. More precisely, at each iteration $i \in [1, h]$, the component t_i is calculated by the formula $t_i = \mathbf{x} \cdot \mathbf{w}_i$, and then the target y is regressed by OLS on \mathbf{x} . PLS analysis has several advantages [25] including the robustness to the high-dimensional problem³ and the ability to eliminate the multicollinearity problem⁴ [26]. These problems are likely to arise on small corpora of texts with a large number of words as in our case. The PLS method is extended and successfully applied for various regression problems [25] or classification of data in general [27–29], and of texts in particular [30].

4.2. The Gini covariance operator

Schechtman and Yitzhaki [31] have recently generalized the Gini covariance operator, *i.e.* co-Gini, in order to impose more or less weight at the tails of distributions. This Gini covariance operator is given by:

$$\text{cog}(x_\ell, x_k) := \text{cov}(x_\ell, F(x_k)) = \frac{1}{N} \sum_{d=1}^N (x_{d\ell} - \bar{x}_\ell)(F(x_{dk}) - \bar{F}_{x_k}), \quad (1)$$

³ When the number of predictors is very large compared to the number of training examples ($N \ll m$).

⁴ Multicollinearity is a problem that arises when certain forecast variables in the model measure the same phenomenon.

where $F(x_k)$ is the cdf of variable x_k . Let us denote $r_k = (R_{\downarrow}(x_{1k}), \dots, R_{\downarrow}(x_{Nk}))$ the vector decreasing rank of variable x_k , in other words, the vector which assigns the lowest rank (1) of the observation with the highest value x_{dk} , and so on:

$$R_{\downarrow}(x_{dk}) := \begin{cases} N + 1 - \#\{x \leq x_{dk}\} & \text{no similar observation} \\ N + 1 - \frac{\sum_{d=1}^p \#\{x \leq x_{dk}\}}{p} & \text{if } p \text{ similar observations } x_{dk}. \end{cases}$$

The generalized co-Gini operator is given by Schechtman and Yitzhaki [31]:

$$\text{cog}_{\nu}(x_{\ell}, x_k) := -\nu \text{cov}(x_{\ell}, r_k^{\nu-1}); \nu > 1. \quad (2)$$

147 The role of the co-Gini operator can be explained as follows. When $\nu \rightarrow 1$, the variability of the
148 variables is attenuated so that $\text{cog}_{\nu}(x_k, x_{\ell})$ tends to zero (even if the variables x_k and x_{ℓ} are strongly
149 correlated). On the contrary, if $\nu \rightarrow \infty$ then $\text{cog}_{\nu}(x_k, x_{\ell})$ allows you to focus on the distribution tails x_{ℓ} .
150 The use of the co-Gini operator attenuates the influence of outliers, because the rank vector acts as an
151 instrument in the regression of y on x (regression by instrumental variables) [32].

152 Thus, by proposing a Gini-PLS regression based on the ν parameter, we can calibrate the coefficient
153 ν of the co-Gini operator in order to dilute the influence of the outlying observations. This generalized
154 Gini-PLS regression becomes a regularized Gini-PLS regression where the parameter ν plays the role
155 of a regularization parameter.

156 4.3. Generalized Gini-PLS regressions

157 The first Gini-PLS algorithm was proposed by [11]. We describe below the new Gini-PLS algorithm
158 based on the generalized co-Gini operator. The generalized Gini-PLS algorithm is depicted in Figure 4.

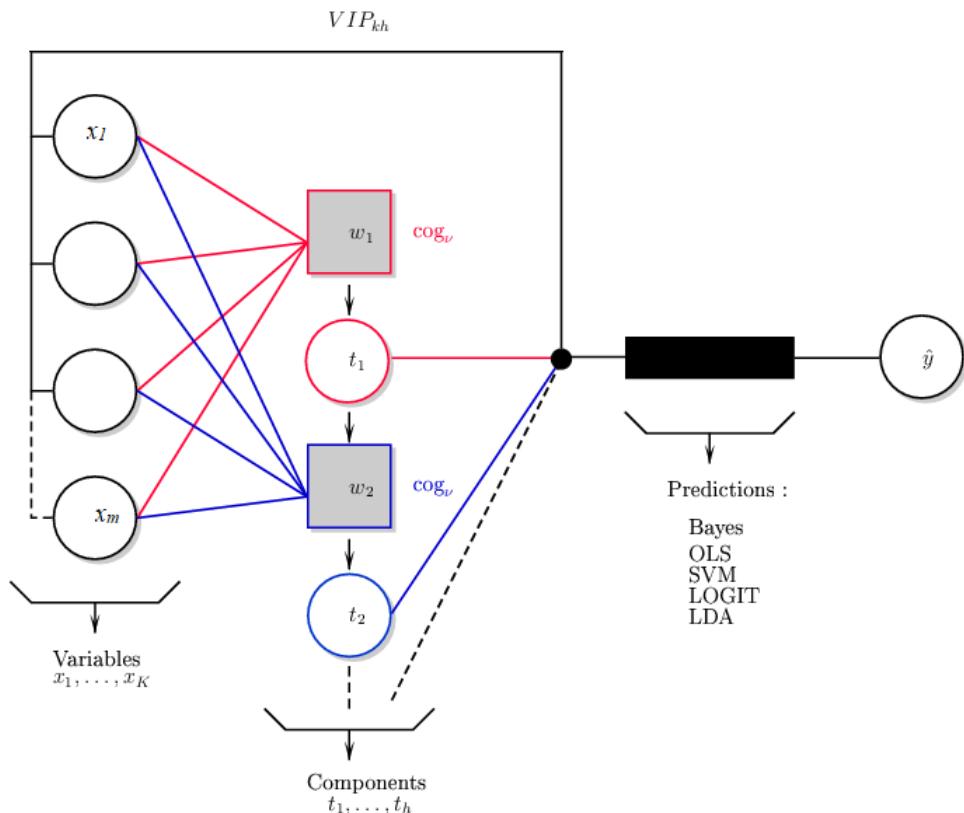


Figure 4. Generalized Gini-PLS algorithm

Step 1: A weight vector \mathbf{w}_1 is first built to improve the link (in the co-Gini sense) between the predicted variable y and the predictors \mathbf{x} :

$$\max \text{cog}_v(y, \mathbf{x}\mathbf{w}_1), \text{ s.t. } \|\mathbf{w}_1\|_1 = 1.$$

The solution of this program is:

$$\mathbf{w}_1 = \frac{\text{cog}_v(y, \mathbf{x})}{\|\text{cog}_v(y, \mathbf{x})\|_1}.$$

As in the standard PLS case, the target y is regressed by OLS on the first component $t_1 = \mathbf{x}\mathbf{w}_1$:

$$y = \hat{c}_1 t_1 + \hat{\epsilon}_1.$$

Step 2: The rank vector of each regressor $R_{\downarrow}(x_k)$ is regressed by OLS on t_1 (with residuals $\hat{\mathbf{u}}_1$):

$$R_{\downarrow}(\mathbf{x}) = \hat{\beta} t_1 + \hat{\mathbf{u}}_1.$$

The second component t_2 is given by:

$$\max \text{cog}_v(\hat{\epsilon}_1, \hat{\mathbf{u}}_1 \mathbf{w}_2) \text{ s.t. } \|\mathbf{w}_2\|_1 = 1 \implies \mathbf{w}_2 = \frac{\text{cog}_v(\hat{\epsilon}_1, \hat{\mathbf{u}}_1)}{\|\text{cog}_v(\hat{\epsilon}_1, \hat{\mathbf{u}}_1)\|_1} \implies t_2 = \hat{\mathbf{u}}_1 \mathbf{w}_2.$$

Thereby, the components $t_1 \perp t_2$ allow a link to be established between y and \mathbf{x} by OLS:

$$y = \hat{c}_1 t_1 + \hat{c}_2 t_2 + \hat{\epsilon}_2.$$

Step h: Partial regressions are run up to t_{h-1} :

$$R_{\downarrow}(\mathbf{x}) = \beta t_1 + \dots + \gamma t_{h-1} + \hat{\mathbf{u}}_{h-1}.$$

Then, after maximisation:

$$\mathbf{w}_h = \frac{\text{cog}_v(\hat{\epsilon}_{h-1}, \hat{\mathbf{u}}_{h-1})}{\|\text{cog}_v(\hat{\epsilon}_{h-1}, \hat{\mathbf{u}}_{h-1})\|_1} \implies t_h = \hat{\mathbf{u}}_{h-1} \mathbf{w}_h,$$

we have by OLS,

$$y = \hat{c}_1 t_1 + \dots + \hat{c}_h t_h + \varepsilon_h.$$

A cross validation makes it possible to find the optimal number of $h > 1$ components to retain. To test for a component t_h , we compute the model prediction with h components including document d , \hat{y}_{h_d} , and then without document d , $\hat{y}_{h_{(-d)}}$. The operation is repeated for all d varying from 1 to N : each time we remove the observation d and we re-estimate the model. To measure the significance of the model, we measure predicted residual sum of squared issued from the model with h components:

$$\text{PRESS}_h = \sum_{d=1}^N \left(y_d - \hat{y}_{h_{(-d)}} \right)^2.$$

The sum of squared residuals of the model with $h - 1$ components is:

$$\text{RSS}_{h-1} = \sum_{d=1}^N \left(y_d - \hat{y}_{(h-1)_d} \right)^2.$$

The test statistics is:

$$Q_h^2 = 1 - \frac{\text{PRESS}_h}{\text{RSS}_{h-1}}.$$

The component t_h is retained in the analysis if $\sqrt{PRESS_h} \leq 0,95\sqrt{RSS_h}$. In other terms, if $Q_h^2 \geq 0,0975 = (1 - 0,95^2)$, t_h is significant in the sense that it improves the power of prediction of the model. In order to test for t_1 , we use:

$$RSS_0 = \sum_{d=1}^N (y_d - \bar{y})^2 .$$

As in the standard PLS regression, the VIP_{hj} statistic is measured in order to select the word x_j which has the most significant impact on the decision y . The most significant words are those including $VIP_{hj} > 1$ with:

$$VIP_{hj} := \sqrt{\frac{m \sum_{\ell=1}^h Rd(y; t_\ell) w_{\ell j}^2}{Rd(y; t_1, \dots, t_h)}}$$

and

$$Rd(y; t_1, \dots, t_h) := \frac{1}{m} \sum_{\ell=1}^h \text{cor}^2(y, t_\ell) =: \sum_{\ell=1}^h Rd(y; t_\ell).$$

with $\text{cor}^2(y, t_\ell)$ is Pearson's correlation between y and component t_ℓ . This information is back propagated into the model (only once) in order to obtain the optimal number of components (on training data). The target variable y is then predicted as follows:

$$\text{category}(x) = \begin{cases} 0 & \text{if } \hat{y} < 0.5 \\ 1 & \text{otherwise.} \end{cases}$$

¹⁵⁹ 4.3.1. Generalized LOGIT-Gini-PLS

¹⁶⁰ As can be seen in the generalized Gini-PLS algorithm, the weights w_j come from the generalized
¹⁶¹ co-Gini operator applied to a Boolean variable $y \in \{0, 1\}$. In order to find the weights w_j which
¹⁶² maximize the link between the words x_j and the decision y , we propose to use the LOGIT regression,
¹⁶³ in other words, a sigmoid which is better adapted to Boolean variables. Thus, in each step of the
¹⁶⁴ Gini-PLS regression we replace the maximization of the co-Gini by measuring the following conditional
¹⁶⁵ probability:

$$P(y_d = 1 / \mathbf{x} = \mathbf{x}_d) = \frac{\exp \{ \mathbf{x}_d \beta \}}{1 + \exp \{ \mathbf{x}_d \beta \}} \quad (\text{LOGIT})$$

where \mathbf{x}_d is the d -th line of the matrix \mathbf{x} of the predictors (being the words in judgment d). The estimation of the vector β is done by maximum likelihood. Therefore, at each step h of the PLS algorithm, the weights w_h are derived as follows:

$$\mathbf{w}_h = \frac{\beta}{\|\beta\|_2}$$

¹⁶⁶ The generalized LOGIT-Gini-PLS algorithm is depicted in Algorithm 1.

¹⁶⁷ 5. Experiments and results

¹⁶⁸ We discuss the performance of various popular algorithms and the impact of data quantity and
¹⁶⁹ imbalance, heuristics, and explicit restriction of judgments to sections related to the request category, as
¹⁷⁰ well as their ability to ignore other requests for the judgment. These experiments also aim to compare
¹⁷¹ the effectiveness of Gini-LOGIT-PLS compared to other machine learning analyses. As in Im *et al.* [33],

Algorithm 1: Generalized LOGIT-Gini-PLS (training)

Data: \mathbf{x} (predictors), h_{max} (maximal number of components), ν_{max} (maximal value of ν)
Result: Principal components t_1, \dots, t_{h^*}

```

1 repeat
2   if  $h == 1$ : LOGIT equation  $P(y/\mathbf{x}) \Rightarrow \mathbf{w}_1 = \frac{\beta}{\|\beta\|_2} \Rightarrow t_1 = \mathbf{x}\mathbf{w}_1$  ;
3   repeat
4     for  $h > 1$  ;
5     OLS equation:  $R_{\downarrow}(\mathbf{x}) = \beta t_1 + \dots + \beta t_{h-1} \Rightarrow \hat{\mathbf{u}}_{h-1}$  ;
6      $\tilde{\mathbf{x}} := (\hat{\mathbf{u}}_{h-1}|t_1, \dots, t_{h-1}) \Rightarrow$  LOGIT equation  $P(y/\tilde{\mathbf{x}}) \Rightarrow$  weights  $\mathbf{w}_h = \frac{\beta}{\|\beta\|_2} \Rightarrow$ 
7      $t_h = \hat{\mathbf{u}}_{h-1}\mathbf{w}_h$  ;
8     OLS equation :  $y = \sum_h c_h t_h + \varepsilon_h$  ;
9     until  $h = h_{max}$  [ $h = h + 1$ ];
10    Compute  $VIP_{kh}, Q_h^2$  ;
11    Choose the optimal number of components  $h^*$  ;
12 until  $\nu = \nu_{max}$  [ $\nu = \nu + 0.01$ ];
13 Dede the optimal parameter  $\nu^*$  which minimizes the error ;
14 return  $t_1, \dots, t_{h^*}, \nu^*$ ;
```

172 we compare different combinations of classification algorithms and term weighting methods (used for
173 text representation). These combinations represent over 600 experienced configurations including:⁵

- 174 • 12 algorithms of classification: Naive Bayes (NB), Support Vector Machine (SVM), K -nearest
175 neighbors (KNN), Linear and quadratic discriminant analysis (LDA / QDA), Tree, fastText,
176 Naive Bayes SVM (NBSVM), generalized Gini-PLS (Gini-PLS), Logit-PLS [34], generalized
177 LOGIT-Gini-PLS (GiniLogitPLS), and the usual PLS algorithm (StandardPLS);
178 • 11 global weighting schemes (cf. Table 5): $\chi^2, dbidf, \Delta_{DF}, dsidif, gss, idf, ig, mar, ngl, rf, avg_{global}$
179 (mean of the global metrics);
180 • 6 local weighting schemes (cf. Table 6): $tf, tp, logtf, atf, logave$, et avg_{local} (mean of the local
181 metrics).

182 *5.1. Assessment protocol*

183 Two evaluation metrics are used: precision and F_1 -measure. To take into account the imbalance
184 between the classes, the macro-average is preferred. It is the aggregation of the individual contribution
185 of each class. It is calculated from the macro-averages of the precision (P_{macro}) and of the recall (R_{macro}),
186 which are calculated according to the average numbers of true positives (\overline{TP}), false positives (\overline{FP}), and
187 false negatives (\overline{FN}) as follows: [35]: $P_{macro} = \frac{\overline{TP}}{\overline{TP} + \overline{FP}}$, $R_{macro} = \frac{\overline{TP}}{\overline{TP} + \overline{FN}}$.

188 The efficiency of algorithms often depends on the meta-parameters for which optimal values
189 must be determined. The *scikit-learn* [36] library implements two strategies for finding these values:
190 RandomSearch and GridSearch. Despite the speed of the RandomSearch method, it is non-deterministic
191 and the values it finds give a less accurate prediction than the default values. The same thing for
192 the GridSearch method, which is very slow, and therefore impractical in view of the large number
193 of configurations to be evaluated. Consequently, the values used for the experiments are the values
194 defined by default (Table 7).

195 *5.2. Classification on the basis of the whole judgment*

196 By representing the entire judgment using various vector representations, the algorithms are
197 compared with the representations that are optimal for them. We note from the results of Table 8 that
198 the trees are on average better on all the categories even if on average the F_1 -measure is limited to

⁵ See <https://github.com/tagnyngompe/taj-ginipls> to have the python code of the Gini-PLS algorithms.

Algorithms	Hyperparameters
SVM	$C = 1.0; \gamma = \frac{1}{ V \times \text{var}(X)}; \text{noyau} = RBF$
KNN	$k = 5$
LDA	$\text{solver} = \text{svd}, n_components = 10$
QDA	
Tree	Gini criterion
NBSVM	$n\text{-grams}$ of 1 to 3 words
Gini-PLS	$h_{max} = 10$
Logit-PLS	$h_{max} = 10$
Gini-Logit-PLS	$h_{max} = 10; \nu = 14$

Table 7. Values of the hyperparameters of the algorithms.

199 0.668. The results of PLS extensions are not very far from those of trees with differences of F_1 -measure
 200 around 0.1 (if we choose the right representation scheme).

Representation	Algorithm	F_1	min	Cat. min	max	Cat. max	$\text{Best}(F_1) - F_1$	max - min	rang
$tf - gss$	Tree	0.668	0.5	<i>doris</i>	0.92	<i>dcppc</i>	0	0.42	1
$tf - avg_{global}$	LogitPLS	0.648	0.518	<i>danais</i>	0.781	<i>dcppc</i>	0.02	0.263	13
$tf - avg_{global}$	StandardPLS	0.636	0.49	<i>danais</i>	0.836	<i>dcppc</i>	0.032	0.346	24
$tf - \Delta_{DF}$	GiniPLS	0.586	0.411	<i>danais</i>	0.837	<i>dcppc</i>	0.082	0.426	169
$tf - \Delta_{DF}$	GiniLogitPLS	0.578	0.225	<i>styx</i>	0.772	<i>dcppc</i>	0.09	0.547	220
-	NBSVM	0.494	0.4	<i>styx</i>	0.834	<i>dcppc</i>	0.174	0.434	
-	fastText	0.412	0.343	<i>doris</i>	0.47	<i>danais</i>	0.256	0.127	

Table 8. Comparison of word representation and algorithms to detect the the judicial outcome.

201 The F_1 average scores of the NBSVM and fastText algorithms generally do not exceed 0.5 despite
 202 being specially designed for texts. It can be noticed that they are very sensitive to the imbalance of data
 203 between the categories (more rejections than acceptances). Furthermore, it is more difficult to detect
 204 the acceptance of the requests. Indeed, these algorithms classify all the test data with the majority label
 205 (meaning) i.e. rejection, and therefore, they hardly detect some request acceptance. The case of the
 206 categories *doris* and *dcppc* for the NBSVM ($F_{1macro} = 0.834$) tends to demonstrate the strong sensitivity
 207 to negative cases of these algorithms since the F_1 -measure of "reject" is always higher than that of
 208 "accept" (Table 9).

209 PLS algorithms systematically exceed the performance (F_1 -measurement) of fastText and NBSVM
 210 from 10 to 20 points. This tends to demonstrate the effectiveness of PLS techniques in their role of
 211 reduction of dimensions. Gini-PLS algorithms do not look any better operate than conventional PLS
 212 algorithms. Presumably the reduction of dimensions is done while still retaining too much noise in the
 213 data. This is confirmed by the results of the trees which remain very mixed for which the F_1 -measure
 214 (0.668) that exceeds barely that of Logit-PLS (0.648). It therefore seems necessary to proceed with
 215 zoning in the judgement that would better identify relevant information and thereby reduce the noise.

216 5.3. Classification based on sections of judgements including the vocabulary of the category

217 Since the judgements relate to several categories of claim, we experiment the restriction of
 218 the judgment to regions including vocabulary of the category of interest: request, result, previous
 219 result (result_a) stated under the terms of the category in the part of the judgment related to the
 220 context (Reasons section). The region-vector representation-algorithm combinations are compared
 221 in Table 10. The results improve enormously with the reductions, except for the category *doris*. The
 222 best restriction combines regions including the vocabulary of the category in the Litigation section
 223 (request and previous result), in the Reasons section (context), and in the Arrangement section (result).
 224 After reducing the size of the judgment, the trees provide excellent results, followed very closely by
 225 our GiniPLS and LogitGiniPLS algorithms. For example, in the *dcppc* category (see Table 5), Tree
 226 performance ($F_1 = 0.985$) slightly exceed the LogitPLS (0.94) and standard PLS (0.934) algorithms. In

Cat.	Algo.	Prec.	Prec. equi.	err-0	err-1	$F_1(0)$	$F_1(1)$	F_{1macro}
<i>dcppc</i>	NBSVM	0.875	0.812	0	0.375	0.916	0.752	0.834
<i>danais</i>	fastText	0.888	0.5	0	1	0.941	0	0.47
<i>danais</i>	NBSVM	0.888	0.5	0	1	0.941	0	0.47
<i>concdel</i>	fastText	0.775	0.5	0	1	0.853	0	0.437
<i>concdel</i>	NBSVM	0.775	0.5	0	1	0.873	0	0.437
<i>acpa</i>	fastText	0.745	0.5	0	1	0.853	0	0.426
<i>acpa</i>	NBSVM	0.745	0.5	0	1	0.853	0	0.426
<i>doris</i>	NBSVM	0.5	0.492	0.167	0.85	0.63	0.174	0.402
<i>dcppc</i>	fastText	0.667	0.5	0	1	0.8	0	0.4
<i>styx</i>	fastText	0.667	0.5	0	1	0.8	0	0.4
<i>styx</i>	NBSVM	0.667	0.5	0	1	0.8	0	0.4
<i>doris</i>	fastText	0.523	0.5	0	1	0.686	0	0.343

0 = "reject" et 1 == "accept"

Cat.: Categories of claim

Algo. : algorithm

err-0: error rate of "reject"

err-1: error rate of "accept"

Prec.: global precision ($accuracy = \frac{TP}{N}$)

Prec. equi.: $\frac{1}{2}(accuracy(0) + accuracy(1))$

Table 9. Evaluation of fastText and NBSVM for detecting judicial outcomes for each claim category.

Category	Region	Representation	Algorithm	F_1
<i>acpa</i>	demande_resultat_a_resultat_context	$tf - dbidf$	Tree	0.846
	litige_motifs_dispositif	$tf - dbidf$	StandardPLS	0.697
	litige_motifs_dispositif	$tf - avg_{global}$	LogitPLS	0.683
<i>concdel</i>	litige_motifs_dispositif	$tf - gss$	Tree	0.798
	motifs	$tf - idf$	GiniLogitPLS	0.703
	context	$logave - dbidf$	StandardPLS	0.657
<i>danais</i>	demande_resultat_a_resultat_context	$avg_{local} - \chi^2$	Arbre	0.813
	demande_resultat_a_resultat_context	$atf - avg_{global}$	LogitPLS	0.721
	demande_resultat_a_resultat_context	$atf - avg_{global}$	StandardPLS	0.695
<i>dcppc</i>	demande_resultat_a_resultat_context	$tf - \chi^2$	Tree	0.985
	demande_resultat_a_resultat_context	$tf - \chi^2$	LogitPLS	0.94
	litige_motifs_dispositif	$tp - mar$	StandardPLS	0.934
<i>doris</i>	litige_motifs_dispositif	$tp - dsidif$	GiniPLS	0.806
	litige_motifs_dispositif	$tp - dsidif$	GiniLogitPLS	0.806
	litige_motifs_dispositif	$atf - ig$	StandardPLS	0.772
<i>styx</i>	motifs	$tf - dsidif$	Arbre	1
	demande_resultat_a_resultat_context	$logave - dsidif$	GiniLogitPLS	0.917
	litige_motifs_dispositif	$tf - rf$	GiniPLS	0.833

Table 10. Impact de la restriction des judgments à certains passages sur l'identification du sens du résultat.

the category concdel, Tree performance ($F_1 = 0.798$) is still closely followed by GiniLogitPLS (0.703) and standard PLS (0.657) algorithms.

The most interesting case concerns neighborhood disturbances (doris category). These judgements often involve multiple information that is sometimes difficult to synthesize, even for a human. The argumentation exposed in *doris* is related to multiple information (problems of views, sunshine, etc.) so that the factual elements that condition the identification of the judicial outcomes are sometimes complex. These information can be either under-represented or over-represented depending on the vectorization scheme. Our GiniPLS algorithm (like our GiniLogitPLS) seems to be particularly suitable for this category of request. The F_1 -measures found in this category amount to 0.806 (for GiniPLS and GiniLogitPLS) and 0.772 for StandardPLS while the trees of decisions are not part of the relevant algorithms for this category of request (no allowed the best three algorithms). This result reinforces the

238 idea that our GiniPLS algorithms can sometimes compete with the decision trees that act as reference
239 in the literature. This result would make it possible in the future to consider including our GiniPLS
240 algorithms in set methods to broaden the spectrum of algorithms robust to outliers and which at the
241 same time play a role of compression of data.

242 6. Conclusion

243 This article attempts to simplify the extraction of the meaning of the result rendered by the judges
244 on a request for a given claim category. It consists in formulating the problem as a task of classifying
245 judgments. Ten classification algorithms have been tested on 55 methods of vector embeddings. We
246 have noticed that the classification results are mainly influenced by 3 characteristics of our data. First
247 of all, the very small number of training examples disadvantages certain algorithms (sensitivity to
248 outliers), such as fastText, which requires several thousand examples to update its parameters. Then,
249 the strong imbalance between the classes ("accept" vs. "reject") makes it difficult to recognize the
250 minority class which is generally the "accept" class. The strong gap between the errors on "reject" and
251 those on "accept", as well as the good results obtained on *dccpc* constitute an evidence. Finally, the
252 presence of other categories of demand in the judgment degrades the efficiency of the classification
253 because the algorithms do not manage alone to find the elements in direct relation with the chosen
254 category. This is demonstrated by the positive impact of the restriction of the content to be classified in
255 certain particular regions of the decision, even if the appropriate restriction depends on the category.

256 Finally, the decision trees are suitable for the task, but the use of Gini-PLS and Gini-Logit-PLS
257 makes it possible to obtain performances fairly close to those of trees and sometimes higher. It would
258 be interesting to combine these variants of PLS algorithms, with others ones such as Sparse-PLS which
259 could perhaps help to solve the problem of vectors of zeros. There are also a large number of neural
260 architectures for the classification of judgment and very large numbers of term weighting metrics
261 for the representation of texts, but none seems to fit all categories. Therefore, a study on the use of
262 semantic embedding representations like Sent2Vec [37] or Doc2Vec [38] would be interesting.

263 **Author Contributions:** This article is drawn from a Chapter of Gildas Tagny-Ngompé's Ph.D. dissertation.

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342 **Sample Availability:** Samples of the compounds are available from the authors.

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