Towards a New Approach for Building Trust and Confidence in Machine Learning Data and Models: Based on an Integration of Artificial Intelligence and Blockchain (Part 2)

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Towards a New Approach for Building Trust and Confidence in Machine Learning Data and Models: Based on an Integration of Artificial Intelligence and Blockchain (Part 2)

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Sentiments and opinions trends analysis and study are two important disciplines of Big Data exploitation. In our case related to Business Intelligence (BI), they make it possible to detect and extract relevant information from raw unstructured textual data, which we call: Textual Business Intelligence (TBI). It is in this context that we propose a new approach allowing to build trust and confidence in machine learning data and therefore in models: based on an integration and a convergence of artificial intelligence and Blockchain. This second part of the article will be dedicated to our approach and the technological integration.

Keywords: artificial intelligence, blockchain, machine learning, neural models, sentiments analysis, text mining

INTRODUCTION

The current project is part of the natural evolution of the researches carried out in our main research domain in its general strategy on Business Intelligence (BI), and in its orientation relative to the exploitation of Big Data. In this context, data comes mainly from users/customers sentiments and opinions, expressed via social medias, forums, blogs, sales sites, etc., on all kinds of subjects such as events, products, attitudes, etc., to express their feelings and experiences.

Analysing sentiments and experiences of users is a major problematic for companies. Several studies and statistics confirm that more than 80% of Internet users consult the comments and opinions of former users before making their own purchases. Recommendations influence our opinions on products, services, etc. and therefore influence our purchases. Companies consequently have a great interest in understanding their customers feedback and comments. They must invest massively in intelligent systems allowing automatic sentiments analysis and opinions mining, in order to be helped to adapt to users' requirements and improve their profits; in the new open world of business and economic intelligence which is the web. Despite advances in this area, several recent studies show that only 29% of companies use data in their decision. This is due to several problems, mainly related to the nature of the existing solutions which are not yet mature enough, and to their costs, which are still too expensive to implement.

The phenomena of business data analysis in the context of "Big Data", for intelligence purposes, concerned mainly the static aspects of textual data models.

However, due to their nature in this context, data as well as their characteristics are "naturally" dynamic and therefore their handling is necessary. The analysis of dynamic aspects of data such as the study & extraction of indicators and the analysis & prediction of their behaviour over time, has become a major issue encouraging the emergence of new research projects, moreover difficult and complex. This complexity can be amplified if data additionally includes specific information such as anomalies, fake information, etc. In fact, the latter, which can alter the judgment and the perception that we can have on the real facts, must be considered in the treatment processes. Detecting and managing these elements is an important task for the dynamic data analysis and for the impact on the associated target indicators trends.

It is in this context that we carried out the current research project, on the dynamic data analysis, entitled:

> "Designing a new approach to build trust and confidence in machine learning data and models: based on an integration and the convergence of artificial intelligence and Blockchain"

In this project, we are interested in the issues of detecting anomalies & false information and their causes in the dynamic sentiments influencing the trends prediction in associated time series/sequences, by proposing a solution, which can limit them, based on a security, certification, etc. data system, via Blockchain.

The main objectives of the project can be recalled as follows:

- Minimize the role and the intervention of a human user, in the context of big data; where processing by a human being is almost impossible to perform (large amount of data). The system should be able to "extrapolate" by exploiting a minimum of annotated & classified (pre-treated) data and learn by it itself the latent science contained in the text, in order to extract all the useful information for decision-making.
- Design and develop approaches considering the dynamic aspects of data.
- Design and develop approaches to detect anomalies and fake information in data.
- Model the prediction of targeted indicators behaviour considering anomalies and fake information.
- Study a solution that can prevent fake information, build confidence and trust in data and make reliable analysis and predictions.

OUR APPROACH

General Context

This section recalls the general context of the research work; in terms of problematics, activities, and their evolution. We can summarize it as follows:

Indeed, we can recall that for several years we have been carrying out several industrial projects on the analysis and exploitation of structured data and more precisely on business intelligence (BI) on databases. The evolution of computerized systems and uses, generating large quantities of heterogeneous data and nonexistent or complex data models, has forced us to extend our activities to consider all kinds of data (not only structured) by integrating semantic analysis of unstructured data, specifically textual.

Our objective in the current work is, on the one hand, to ensure & assume the evolutions requirements of new information systems related mainly to prediction based on certified reliable data; and on the other hand, to weave links guaranteeing coherence between different fields: completely different, but complementary. These “natural” evolutions are essential for considering new problems related to data management such as those of Digital Humanities, Big Data…; where unstructured data representing more than 80% (according to several published studies), must be considered and exploited.

Our work is divided into the following approach categories (in chronological order):

- Design and develop approaches considering the dynamic aspects of data
    - Extension of classic data models to support dynamic data behavior

    - Design solutions supporting dynamic data models
- Study and propose solutions to detect anomalies and fake information
    - Exploitation of new dynamic data models for anomalies and fake information detection
    - Design of technological solutions for anomalies and fake information detection
- Create a solution capable of predicting targeted indicators behaviors according to an enriched criteria model
    - Integration of fake information in the prediction process
    - Integration of elementary (partial) predictions of various constituents and time blocks for the calculation of the global prediction
- Implement a solution based on generating trust in data and treatments that can prevent fake information
    - Study of different possibilities for data guarantee
    - Study of an approach based on the integration of artificial intelligence and "Blockchains" for data certification and trust generation
- Design solutions improving performances of certain current systems
    - Exploitation of Deep Learning in the context of prediction from unstructured data
    - Definition, extraction and exploitation of dynamic language models and enriched models for prediction
    - Instantiation of the different models
    - Development and implementing of different tools and modules

Difficulties Encountered, Circumventions, Abandonments

For the realization of this work, several difficulties were encountered: those related to modeling and formalization of textual data processing for prediction, then those related to technological choices and data-processing realizations.

In the first case, our first approach was to enrich existing models for predicting time series as well as basic models. The goal is to use them in the context of sentiments and opinions prediction for BI. Subsequently, several other difficulties appeared. They are due to the specificities of prediction from comments and recommendations texts written mainly in specific languages including SMS, Acronyms, Irony, Metaphor, ...; which are normally different from those of natural language texts. This forced us to initiate new and extensive research in collaboration with BI and intelligence specialists to study these characteristics to improve our models.

During the experiments, we noticed that, the richer the models, the better the results of analyzes. What encouraged us to deepen research in the field in order to identify new characteristics, to design semantic and temporal models rather rich for use of language variations and to set up solutions allowing their detection and their extraction.

In the second case, on the technological level, several problems were also encountered. They mainly concern the technological choices. We used, for example, at first the “advanced” technological models, based on “dense” semantic vector representations: “Word Embeddings” and its implementation “Word2vec”. They represent words as vectors in semantic vector spaces of small dimensions (around 300) very practical and optimized for calculations; unlike other models such as the one-hot which represents words in spaces of vocabulary-size dimensions. The problem is that these existing Word Embeddings representations have been trained on texts whose semantics are not necessarily linked to the specific area of BI. In order to get around this problem, we were forced to change the technological language model, and we chose to adopt new "dense" vector representations, trained on corpora in the studied domain.

We have also improved this basic representation model by incorporating parameters (Features) such as the intermediate prediction of each characteristic; which is not used in existing models. This makes it possible to capture intermediate predictions that can help better predict overall behavior. We have also used technologies that have already proven themselves in the Automatic Natural Language Processing, by adapting them to the field of BI.

Still on the technological level, several platforms and classifiers have been tested and abandoned before making the choice to improve and exploit a deep neural network, in this case a recurrent neural network (RNN) and it version long-short term memories (LSTM), for Automatic Natural Language Processing (NLP).

We have encapsulated several elements, described later in this document, in a sophisticated analysis process allowing the conversion of all kinds of data (including unstructured), into structured, contextualized and unambiguous data. Once processed, this data becomes easily exploitable, relevant and of high quality, called Smart Data; well suited to specific situations and uses. By applying it to a concrete case, in this case to BI, we were able to show our approach contribution to circumvent certain problems of sentiments prediction, related to the specificities of commentaries, sentiments, opinions, etc. This study has been validated by experiments optimizing a solution for which some aspects of the results have been confirmed by several publications in journals and international conferences.

This work has allowed us, on the one hand, to deepen formalization and to consider certain important characteristics of natural language use for predicting BI indicators; and on the other hand, to exploit certain advanced technologies on which we have made improvements. Thanks to all these elements, we were able to improve certain results in this domain.

Scientific and Experimental Approach

In our approach, the scientific and the experimental approach are of two kinds. Those who deal with problems relating to content for the management of time series prediction, then those who consider the technological problems processing.

Supported Elements

This part recalls the various problems and lacks addressed in our approach. In a way, that will complement the previous section describing the meet difficulties.

Technological Point of View. The supported technological elements concern:

- Neural networks: the limits, which we will detail little later in this part, of conventional neural networks and their "Recurrent" version, forced us to adopt and improve an implementation of this kind of network, in this case LSTM network (Long-Short-Term Memory).
- Characteristics: for definition and generation of characteristics, we propose to deploy our data model (described below) to obtain discriminating behavior characteristics (Features) influencing the prediction.
- Machine learning: we trained the system on several possible combinations of attributes to deduce the good prediction and configuration; and did the same for validation and tests.

Content Point of View. Among the elements supported on the content side, there are:

- Correction of the prediction at the level of the constituent elements:
  - Learn and correct the prediction in the context
- Detection of the global behavior prediction:
  - Learn the prediction of global classes (classification)
- Data authenticity:
  - Identify data sources and build trust
- Text normalization:
  - Support for abbreviations, acronyms and non-compliance with linguistic rules
- Multilingualism:
  - Develop solutions that can work for languages other than English.

Building of General Solution

Our contribution can be summarized in a few words as follows. In addition of being based on researches improving existing language models, allowing to characterize as much as possible the texts, their words, their uses and their meanings, their behaviors and consequently making it possible to improve their

analyzes, their interpretations and their prediction in the context of BI; is based on deep learning of extended representation models of sentiments analysis and prediction. As in the previous section, this part will be divided into two: one devoted to the technological level solution presentation, the other to the content level solution presentation.

Building Technological Elements

On this part, our approach consists on the integration of Blockchain allowing to trust previously defined aspects of a sentiment (sentiments, author, entity, etc.) in addition to intermediate predictions (see hereafter) which have the advantage of characterizing the information in a secure manner (fake or not) early upstream of the process.

A considerable difference between the predicted value and the actual value provided by the next block in the Blockchain makes it possible to alert of possible fake information. Certifying authors can also prevent the proliferation of fake information. Overall, this integration of the Blockchain makes it possible to consider fake information in the process as well as its prevention.

We will see later in the document that the adoption of Blockchain technology also makes it possible to secure, certify and deal with fake information and therefore build trust in data.

This technology also has the advantage of correcting the predicted values at a time t using the calculated values from the next block in the chain. This optimizes the global prediction system in an unsupervised manner. All these elements together enrich a new version of instances allowing to refine the global prediction (we will come back to this in the part dedicated to our contribution).

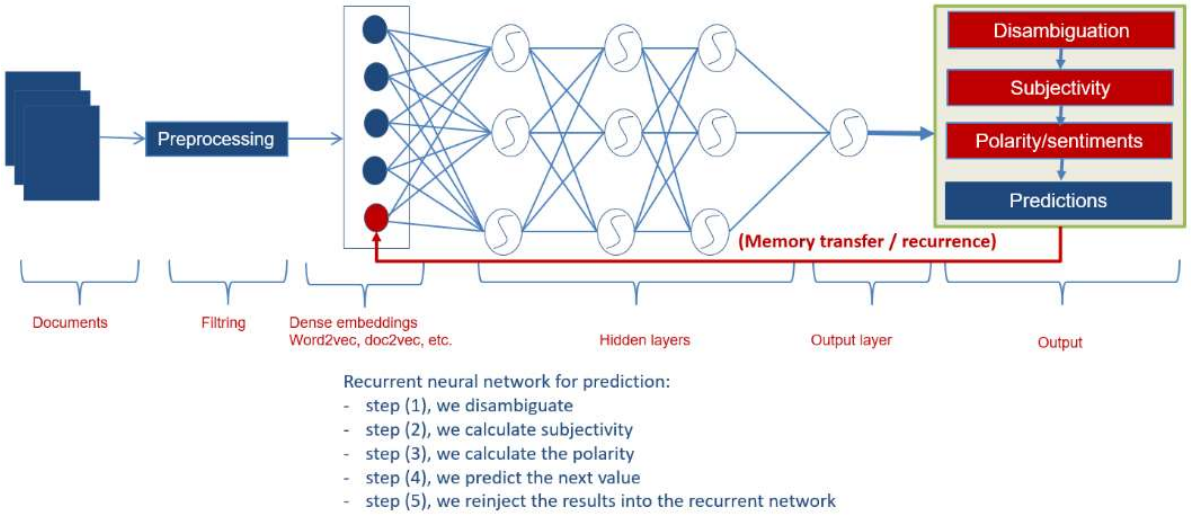
In order to better describe the technological part of the solution, we will present the basic technological modules on which it was built, giving reasons for the made choices.

Adoption & Adaptation of a Deep Learning Architecture. Deep architectures are networks with several layers, which can model data models with a high level of abstraction, articulated around non-linear transformations.

We made this architecture choice because, we tested and exploited them successfully in the case of natural language processing and for static sentiments analysis; and that we think they should also be better suited to predicting behavior. During our work, we tested several configurations, some of which generated many difficulties and/or were abandoned; because of certain combinations and layouts of layers based on symbolic and numerical learning models. The location of symbolic models in the general process was an issue; because they are difficult to set up, except for very limited areas. A text must be represented there by the words constituting it as well as by the properties resulting from the various linguistic treatments or specific formalizations such as ontologies. The difficulty lies, as has been described previously, in the fact that one cannot model and describe, a priori, and in a complete manner the entire domain. This would require a lot of resources and knowledge, and therefore a lot of work.

To get around these difficulties, we favored the integration of unsupervised models upstream of the process. These models are based on mathematical calculations in optimized, well-adapted semantic spaces (see paragraph above on the difficulties encountered). The advantage is that there is no need for pre-processed information; we directly use the data to be analyzed and the mathematical models to deduce the models, their representations and their instantiation.

FIGURE 2
ADAPTED DEEP ARCHITECTURE FOR SENTIMENTS ANALYSIS AND PREDICTION



Concretely, the adaptations can be recalled as follows:

- The first layers were devoted to the extraction of latent semantic and information (Features). They use unsupervised machine learning, exploiting numerical approaches based on word frequencies and sequencing, and on statistical and probabilistic mathematical models, for coding latent semantics
- The last layers were devoted to decision-making. They use supervised learning, exploiting symbolic approaches based on structured data and their description, generated in the previous layers, to perform the processing.

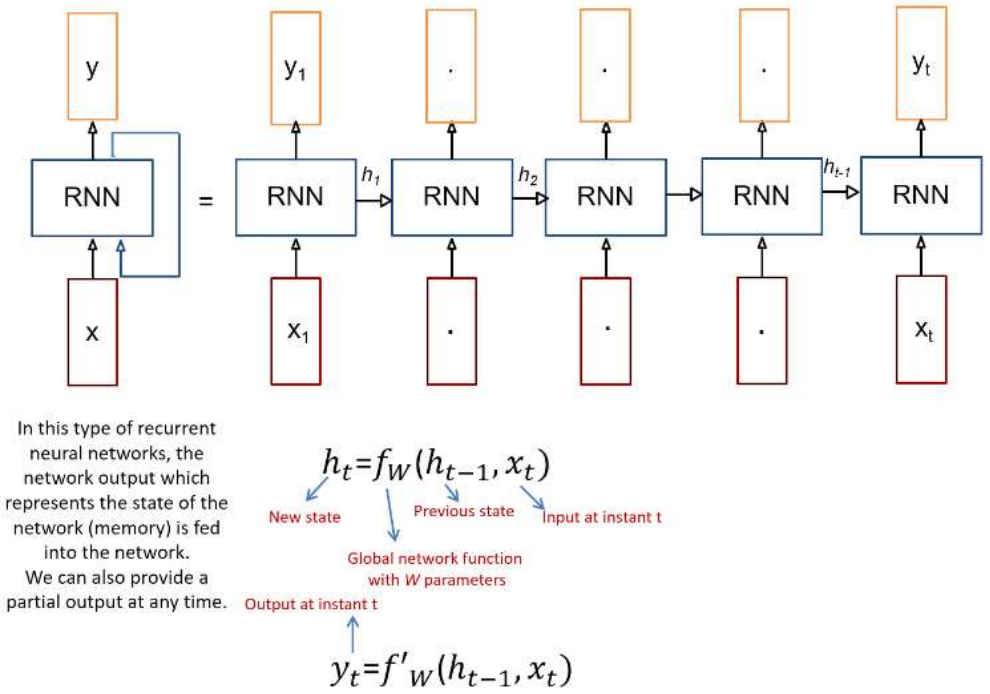
This approach has the advantage of combining the two approaches, at different levels, and with specific moments. Its originality lies in the fact that, on the one hand, it integrates important notions in the model of sentiments prediction as time series; on the other hand, it exploits these notions to generate a semantic model enriched with temporal data aspects on which we apply our machine learning algorithms.

Improvement of a Specific Recurrent Neural Network (RNN): Long-Short-Term-Memory (LSTM). We can summarize the improvements in this part as being an integration of an LSTM in time (time intervals) or in Blockchain blocks.

Several studies have shown that deep learning has been successfully exploited in many fields, including that of automatic natural language processing (NLP). One of the best implementations is the generation of dense semantic vector spaces (Mikolov 2013).

The well-adapted neural networks for NLP are the RNN, have been designed to consider the recurrent and sequential nature of natural language. These networks have the advantage of calculating each state from its previous (historical) state and the new entry. By superimposing them, they can propagate information in both directions: towards the input layers and towards the output layers, thus reflecting an implementation of neural networks, close to the functioning of the human brain where information can propagate in all directions by exploiting the memory principle (cf. the LSTM version of RNN below), via recurrent connections propagating information from subsequent learning (memorized information). These are the characteristics that allow them to consider several important aspects of natural language. Indeed, they have this capacity to capture latent syntactic, semantic, stylistic and orthographic structures, from word order, unlike other technologies such as those based on the concept of bags of word where no order is considered, obviously involving associated information loss.

FIGURE 3
HOW AN RNN WORKS



Each new internal state and each new output depends on the new entry and the old state.

RNNs can also be stacked and bidirectional, and the preceding simple equations can be redefined for both directions and for several learning layers according to the model below.

$$forward: h_t^l = \tanh W_t^l \begin{pmatrix} h_t^{l-1} \\ h_{t-1}^l \end{pmatrix}, h_t^l \in \mathbb{R}^n, W^l dimension\ matrix\ [n \times 2n]\ , t\ time, l\ level\ in\ the\ stack$$

$$backward: h'^l_t = \tanh W'^l_t \begin{pmatrix} h_t^{l-1} \\ h'^l_{t+1} \end{pmatrix}, h_t^l, h'^l_t \in \mathbb{R}^n, W'^l dimension\ matrix\ [n \times 2n]\ , t\ time, l\ level\ in\ the\ stack$$

$$Output: y_t = \tanh W_t \begin{pmatrix} h_t^l \\ h'^l_t \end{pmatrix}, y_t \in \mathbb{R}^n, W^l dimension\ matrix\ [n \times 2n]\ , t\ tme, l\ level\ in\ the\ stack$$

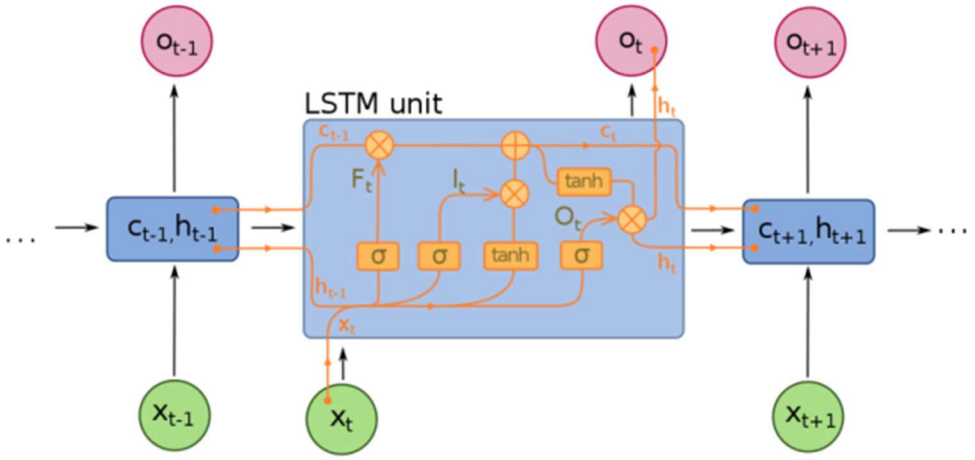
The multi-layers RNN training is done, as for the other types of neuronal networks, by the minimization of the error (difference between the desired output and the obtained output) which one obtains by the backpropagation of the error and the descent of the gradient. It can be demonstrated mathematically that the depth of the RNNs can be high, because of their sequential nature, generally depending on the number of words to be processed; can provoke:

- Either the Vanishment of Gradient in the first layers and the cessation of learning from a certain depth. This is the case where, the gradient is multiplied by a power k (k being the rank in the depth of the network) of a number μ by a matrix of coefficients (Bengio et al. (1994)) with | μ | <1, tends to 0 when k is high.
- Either the explosion of the gradient (Explosion of Gradient) always in the first layers and the end of learning from a certain depth. This is the case where, the gradient is multiplied by a

power k (k being the rank in the depth of the network) of a number μ by a matrix of coefficients (Bengio et al. (1994)) with | μ |> 1, tends to + ∞ when k is high.

The LSTM architecture makes it possible to remedy these problems (Hochreiter, S., & Schmidhuber, J. (1997). It is based on finer control of the information flow in the network, thanks to three gates: the forget gate which decides what to delete from the state (ht-1, xt), the input gate which chooses what to add to the state and the output gate which chooses what we must keep from the state (cf. equations below).

FIGURE 4
HOW AN LSTM WORKS

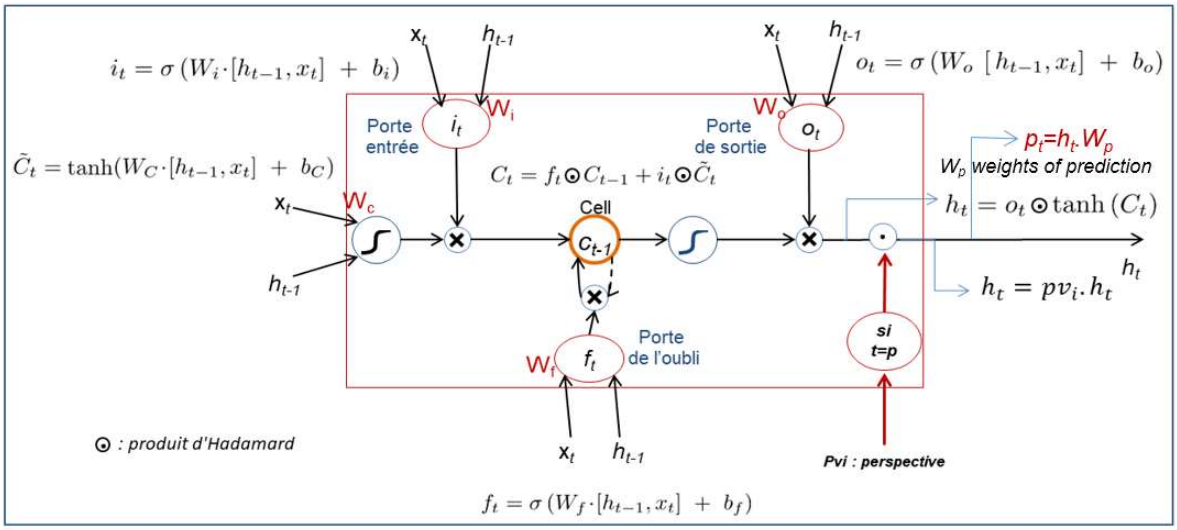


$$F_t = \sigma(W_F x_t + U_F h_{t-1} + b_F) \quad (forget\ gate)$$
$$I_t = \sigma(W_I x_t + U_t h_{t-1} + b_I) \quad (input\ gate)$$
$$O_t = \sigma(W_O x_t + U_O h_{t-1} + b_O) \quad (output\ gate)$$
$$c_t = F_t \circ c_{t-1} + I_t \circ \tanh\,(W_c x_t + U_c h_{t-1} + b_c)$$
$$h_t = O_t \circ \tanh(c_t)$$
$$o_t = f(W_o h_t + b_o)$$

These equations defining the learning process of an LSTM express the fact that this kind of network makes it possible to cancel certain useless information and to reinforce others having a great impact on the results. We can also demonstrate mathematically that this architecture allows, in addition to the optimization of calculations in the network, to solve the problems related to the vanishing and the explosion of the gradient. This is what motivated our choice to use and improve this model by adapting it to our needs.

We have therefore chosen to improve LSTM architecture by optimizing the information propagation of the control gates in the network. In addition to the introduction of the concepts of perspective and attention in the LSTM calculation process, we have added new improvements such as considering the dynamic aspects of the constituent elements, in this case Blockchain blocks (see Blockchain section). At the output of each block, the system can calculate its polarity as well as the prediction of the next block. These predictions are possible for the blocks of the chosen past time interval: [t-p_1, t]. The results show that these elementary predictions improve the prediction of the global behavior, which corresponds in our case to the blocks of the chosen future time interval [t, $t + p_2$].

FIGURE 5
IMPROVED LSTM ARCHITECTURE



Therefore, for Big data needs, the LSTM architecture based initially on 3 gates, has been improved and optimized by integrating in it in addition the concepts of perspective at the output of the network, followed by the concept of attention and the elementary predictions of each block level. The new LSTM model allows to control the transfer of:

- What to use from the input
- What to use from the hidden state
- What to send out
- Depending on the chosen point of view or perspective
- Paying attention to relevant outputs
- And considering the current polarity and the current prediction corrected from the next block in the Blockchain or from the chosen next time interval for temporal data grouping for which we would like to make the prediction

These gates can be used to cancel certain information which is not needed for prediction and to reinforce other. We can demonstrate mathematically that this architecture allows, in addition to the optimization of calculations in the network, adapted to Big Data, and the resolution of the problems related to the vanishing and the explosion of the gradient described above, to consider temporal aspects improving the prediction.

Adoption of Blockchain Technology. The deficiencies described in the sections related to the prevention of fake information and of data quality have led us to study solutions that can help to remedy these problems. Among these solutions, Blockchain is one that we think is very interesting to specifically fill in certain flaws in artificial intelligence (AI) massively exploited. We also believe that AI can also significantly improve and optimize the Blockchain. This is what we will try to show in the rest of the document.

Benefits of Blockchain-based Architectures for Content Creation. The actual social medias solutions centralizing the content creation can enable censorship and/or redirect user's opinions and sentiments trends. We believe that the Blockchain can remedy these problems; Blockchain being a technological approach, allowing several implementations and configurations. For the project purposes, we have privileged and defined an architecture allowing:

- Users to be the owners their content
- Better creation control of the shared content, thanks to decentralized validation
- Protect publications, thanks to the immutable nature of blockchain
- Secure private content by encrypting data and especially associated metadata (identifiers, emails, etc.)

- -…

The goal is that the solution will ultimately allow:

- Increase freedom of expression. Classical encrypting systems can encrypt data, but not associated metadata, Blockchain can do it for both.
- Empower authors. We can justify their writings through authors filters enabled by metadata.
- Target data processing. By exploiting metadata stored in Blockchain, we can process filtered data: by theme, discipline, point of view, date, author, etc.
- Encourage crowdfunding. In the case of content creation for example, we can encourage the quality content creation where authors can be rewarded according to the quality of their content and readers according to the quality of their comments, remarks, etc. This by exploiting Smart contracts.
- Prevent the proliferation of fake information. Increase or decrease user's credibility and popularity according to the quality of their participation in the Blockchain; especially according to what they publish and to their reports for preventing fake information.
- Avoid espionage: exploit private Blockchains to create certified content shared within a specific community.
- …

Blockchain integration With Deep Learning. As our thinking progresses, we propose to integrate Blockchains and Deep Learning along two axes: Blockchain in the service of Deep Learning and (vice-versa) Deep Learning in the service of Blockchain.

Blockchain in the Service of Deep Learning. The integration of Blockchain in the service of AI is done to ensure the authenticity of writings, to avoid opinions and sentiments falsification. Given that data storage is very expensive in Blockchain and that the content (opinions, sentiments, comments, recommendations, etc.) could be large, we proposed to store only metadata (including the references of the content) and Hashes (of metadata and associated content) in the Blockchain; the contents remain outside (so that it is less costly in terms of storage and management). This allows to have the signatures (hashes) of the different content in the Blockchain to avoid data falsification, and metadata to filter them according to usage needs. It is a suitable implementation of the Blockchain in the service of user's feedbacks, which allows machine learning on reliable & certified data generating confidence in terms of data & models.

The integration of Blockchain in the service of AI can also facilitate the sampling and grouping of temporal data via blocks allowing the isolation and the extraction of studied temporal indicators.

AI in the Service of Blockchain. In this area, we studied the integration of AI in the service of Blockchain to allow it better management; namely the use of AI to:

- Resolve and find "smart consensus" in the Blockchain. Learn the consensus Y=f (X): where X = sequence of transactions and Y = (accepted or rejected). An LSTM can be used to calculate consensus weights. This can improve the decision making in the Blockchain.
- Detect abnormal behaviors, attacks, etc. in Blocks and propose the appropriate solutions.
- Smartly adapt time blocks creation according to the number of transactions.
- Learn the models of user's profiles (by analyzing users' machines such as cookies, but without sharing them), the processing is local, and the results are shared anonymously.
- Enrich smart contracts. Currently smart contracts execute simple programs, but by using AI we can implement intelligent programs capable of making well justified and better motivated decisions and judgments through certified content.
- Help to detect and prevent Fake News. Train models on existing Fakes news, then use them. Also, Blockchain can be used so that users who have correctly reported Fake News are rewarded with tokens or reputation coins or scores; those who create them see their reputation diminished (the more credible in the network, see their content more considered and published). This encourage increasing the reliability of data.
- Encourage authors (to create content), readers (to comment, recommend, criticize, etc.) and evaluators (to evaluate), via awards managed by Smart Contracts to create better quality content. When content is created, it is referenced in the blockchain, becomes object to evaluate,

once the evaluations are received, the algorithm decides whether to publish. We can also imagine a collaborative system based on the vote of users with good reputation scores to validate or not information and content: build a trusted network or a reputation network.

- Take inspiration from intelligent and distributed multi-agent models and Blockchain architecture for the implementation of distributed and cooperative Blockchains. This is to optimize processing in Big Data.
- …

Technological integrations in Blockchain Context

Polarities and Predictions in the Context of Blockchain

In our case, for sentiments analysis and prediction, Blockchain must contain a kind of index and metadata which refer to Big Data stored outside the Blockchain. The metadata must contain the user ID and the location reference to the content (stored in dedicated Data Lake). This makes it possible to extract information relating to an indicator behavior & evolution or relating to a user sentiments and opinions, for example.

As a reminder, temporal predictions are of two types:

- Prediction of time series
- Prediction of time sequences

For time series, we extract numerical values from the texts on which we apply the prediction algorithms. We predict a numerical value.

The prediction of time sequences is based on symbolic values and especially of their order in time. It consists in predicting a class or a sequence (multi-class classification).

Our approach concerns the prediction of time sequences for the sentiments, opinions, recommendations, etc. prediction which is based on a "Mapping" between Blochchain architecture and LSTM architecture presented previously. We have made improvements to the bidirectional recurrent neural networks model and their implementation LSTM (Long Short-Term Memory); to support additional elements in the context of this integration (Blockchain, IA), which are not supported in current systems.

More concretely, at an instant t, for the blocks of the past, we implement mechanisms to capture the signals of the elementary predictions of the blocks, really corrected by the polarities of the next blocks and to transfer them to higher levels in order to condition and calculate the global prediction. These mechanisms were enhanced by the integration of the extended context in the calculation of subjectivity conditioning the polarity, improved by a system adjusting local predictions by learning a LSTM to be able to predict the polarities of future blocks.

At the Block level, we have therefore introduced the notion of "attention" at the level of words, sentences and blocks to filter elements according to their relevance (importance) in the polarity calculations. This is a very important concept allowing the relief of treatments in LSTM.

Also, to consider the domain (point of view), we have implemented a mechanism which makes it possible to filter representation vectors in relation to a domain; by calculating a cosines distance between each vector and the considered domain vector(s).

These two elements were added to an elementary predictions system for the correction of the overall predictions system.

All these elements have been integrated into a hierarchical processing architecture at four levels: word, sentence, document and block; allowing the calculation of a faithful representation of each block and the deduction of its class, polarity or sentiments.

FIGURE 7
PREDICTION REFINED AND CONDITIONED BY ELEMENTARY BLOCK PREDICTIONS

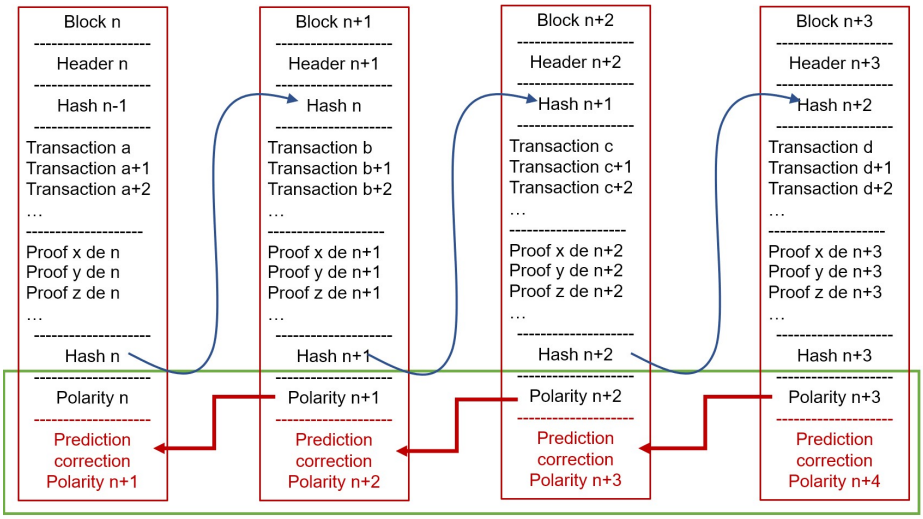
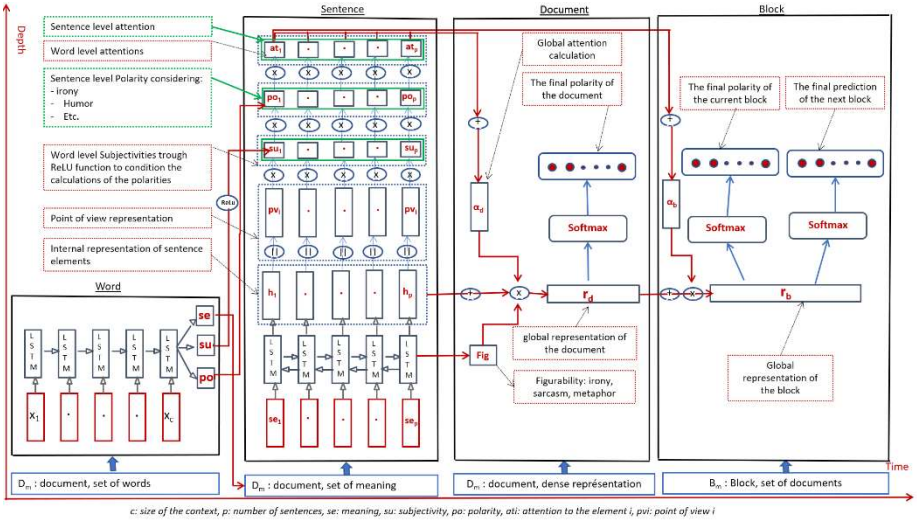


FIGURE 8
GRAPHICAL VERSION OF OUR ALGORITHM



A perspective is a set of words characterizing an analytical point of view (multidimensional space).
Let p be the number of words in the current sentence
Let i be the current perspective index
Let P be a perspective defined by the dimensions $p_1, p_2, \dots, p_l$
Let H be the matrix composed by the hidden representations $h, h_2, \dots, h_p$ *generated by the LSTM*

Consider $pv_i = \sum_1^p d_j$ *où* $d_j = \sum_1^l d_k$ *et* $d_k = \frac{p_k.h_j}{\|p_k\|\|h_j\|}$

pv_i *is a first weighting in the prediction calculation. It is based on the sum of the cosine distances between the hidden representations generated by the LSTM and the dimensions of the targeted analysis perspective.*

This makes it possible to obtain a first transformation, weighted by the comparison with the considered view, of the internal representations of the sentence meanings:
$H^{'} = \left(h_1^{'}, h_2^{'}, \ldots, h_p^{'}\right), o\grave{u}\ h_j^{'} = d_j . h_j$

$d_j is\ the\ sum\ of\ the\ say\ cosines\ of\ hi\ at\ each\ dimension.$

$$\propto_d = softmax(\sum_{1}^{p} at_i)$$

$at_i = w_i^T . h_i^{'}\ constitutes\ the\ learned\ attention\ by\ (w_i) for\ each\ h_i^{'}$
$prediction = H \propto_d^T represents\ the\ output\ of\ the\ system.$ The *figurability is not considered in the current state of the calculations.*

At the block level, the proposed solution consists of several layers for sentiments analysis and prediction:

- Disambiguation,
- Subjectivity,
- Domain / point of view,
- Attention,
- Polarity,
- Prediction
- Correction.

The integration of all technological elements is detailed in the following three main steps:

- The first step of the word level consists in obtaining a dense vector representation (approximately 300 dimensions) of the meaning of each word in the document, in addition to its subjectivity (objectivity) and its polarity. We proceed as follows:
    - extract specific elements of speech to make them undergo specific treatments: expressions, humor, irony, etc., then replace them with their true meanings in the document.
    - project all the words of the obtained document into an appropriate vector space, using "Word Embeddings" technologies and their versions allowing the reduction of dimensions, for example "Word2vec".
    - take up and adapt the proposed algorithm for meaning analysis and extraction from text type content. In addition, parameters characterizing the context influencing the meaning of words in the text, have been integrated and added for sentiments analysis for BI (cf. elements described below). The goal is to train a recurrent neural network (RNN) and its bi-directional implementation LSTM (BI-LSTM) for disambiguation; because we chose the phrase as the semantic splitting. This type of network is necessary, because it is well adapted and allows to exploit the contexts on the right and on the left of each word in the sentence and consequently can disambiguate all the words of a sentence. This approach is unsupervised, because the SentiWordNet knowledge base is used to deduce meaning. We can also make our approach supervised by using annotated corpora. We have chosen SentiWordNet because it allows to provide in addition to the meaning (SynSet), its subjectivity and its polarity; elements that we have used to optimize certain aspects of our approach. For this task, we can also use methods such as: synset2vec, "a method for mapping word sense embeddings to synsets (Alexander Panchenko, 2016)".

- At the end of the previous step, mainly devoted to word level processing, we get a disambiguated document. We think that the subjectivity and therefore the polarity of the words depends on their use in the sentence, and the subjectivity & polarity of the document depend on the sentences constituting it. Therefore, we based, in this part, the continuation of the treatments on sentences. The sentence level processing is the richest and most complex part of our process, some details of which are given below. For each sentence:
    - After splitting into sentences, we send all the meanings (calculated in the previous step) of each sentence to a bi-directional Bi-LSTM to learn a hidden vector representation hi of each word (here of each meaning) in its context of use which is the phrase. This vector is a condensation of the hidden layer's vectors obtained from the forward and backward propagation in the Bi-LSTM network.
    - We previously explained that the notion of domain or point of view is very important in sentiments analysis. Indeed, in the comment "The meal is excellent, and the service is poor", if we analyze this comment from the point of view "cuisine", the comment is positive; but if we analyze it according to the "service", of course the comment is negative. To support this phenomenon, we have concatenated each representation hi with the vector associated with the point of view Pvi; this in order to consider this notion in the calculations. The dot product can be used, it will reflect the distance between the VECTORS and the DOMAIN; which could be used as a weight in calculating polarity.
    - At the end of the previous step, we get a new representation of words meanings in the sentence. In our approach, and in order to simplify the process, we have introduced and improved the concept of attention which allows us to consider in the polarity calculation only important elements. We say paying attention to some important elements in the process, but not to others. Note that in the case of sentiments analysis, attention can be paid to the level of words in the sentence, but also to the level of sentences in the document and at the level of blocks in the Blockchain. In our case, we have integrated all three. We exploited three elements to select the elements to which we must pay attention: the subjectivity of each meaning (calculated in the first stage), the polarity of each meaning (also calculated in the first stage) and an attention of the higher levels considering previous combinations and weights. These elements are of course calculated for words, for sentences and for blocks.
    - At this stage, the prediction of each block is calculated according to the different characteristics previously calculated. We can correct it by the real polarity from the next block, thanks to Blockchain. This step enriches the "classic" characteristics used for predicting overall behavior.
- In this step, we calculate the polarities and global predictions of documents and blocks:
    - We calculate the vectoral representation of the document from the internal representations of sentences (the representations of the hidden layers of the LSTM)
    - We calculate the products to obtain a weighted representation of the document
    - We calculate the overall attention at the document level
    - We calculate the sum of the representations of the documents of a block to obtain a representation of the block
    - We calculate the products to obtain a weighted representation of the block
    - We submit the results to a Softmax (trained function which provides the probabilities) for the calculation of the polarity of the block level.
    - We submit the results to a Softmax (trained function which provides probabilities) for the prediction of the block level.
    - We proceed in the same way for the next block to obtain its polarity
    - We compare and correct the prediction made from the current block

- We cumulate all the results including intermediate predictions to calculate the global prediction

Construction of Content-Oriented Elements

The static sentiments analysis is used in several fields and for different needs and is based on the study of the polarities and subjectivities of words, expressions (phrases), documents (the most common case), corpora, etc. We consider that the study of the dynamic behavior of sentiments must, in addition, to the different analysis levels and to the classic parameters of the static context, exploit temporal aspects including time and dynamic temporal characteristics. Therefore, the overall context of the dynamic aspects can be defined as in the following:

Global context = static context + temporal context (t, current polarity, previous polarities of t-a, following polarities t + b, other temporal characteristics)

As other characteristics in our model, we enrich the calculation of the prediction at an t instant, by a new characteristic which is the predicted value for t+1 instant; in the interval of the chosen past time for training.

Exploitation of Polarities and Subjectivities Lexicons. In terms of dictionaries for BI, as for natural language, the lack of annotated corpora, on the one hand, and the concern to make our approach generic (without being limited to a particular domain), on the other hand, have forced us to implement a strategy based solely on sentiments lexicons. The best known and most used in this domain is SentiWordNet [17]. This particular lexicon was generated by mixed machine learning methods (supervised and unsupervised) and word processing technologies on Wordnet (famous semantic network). In the current project, this "polarized" version of Wordnet [18] was used to complete the instantiation of our extended semantic data model and to build training, validation and test datasets.

Global Semantic Context Model. The notion of semantic context which we are talking about here concerns all the parameters that can influence the meaning and polarity of words in the context of BI and therefore prediction at block level. It is a concept that is difficult to define, because there are no studies today that comprehensively define this concept in general and especially in the domain of BI. We have manually analyzed several comments and recommendations texts from e-commerce sites, to better understand and characterize this kind of document. We made assumptions to test certain parameters; some were selected but others who had no influence in the analysis process were ignored. We have deduced that the context in the field of BI can also be considered as an aggregation of natural language context parameters, augmented by new parameters specific to BI influencing prediction, recalled in this following.

Note that we will only present, in this part, the new parameters which must be combined with those of the natural language to constitute the global context for BI. We have classified them as follows:

- Subjectivity: parameters to represent the subjectivity or not, of a word, a sentence, a document, etc.
- Polarity: parameters to represent the polarity, of a word, of a sentence, of a document, etc.
- Discourse analysis context: parameters to represent aspects of discourse analysis: irony, metaphor, frozen expressions, etc.

Prediction: parameter representing the local prediction of each element (word, sentence, document and block), influencing the global prediction.

The detection of subjectivity consists in determining if a unit language (word, sentence, document) expresses a personal attitude, an opinion, etc. and if so, what is its polarity. In our treatments, the calculation of polarity is conditioned by subjectivity to lighten treatments.

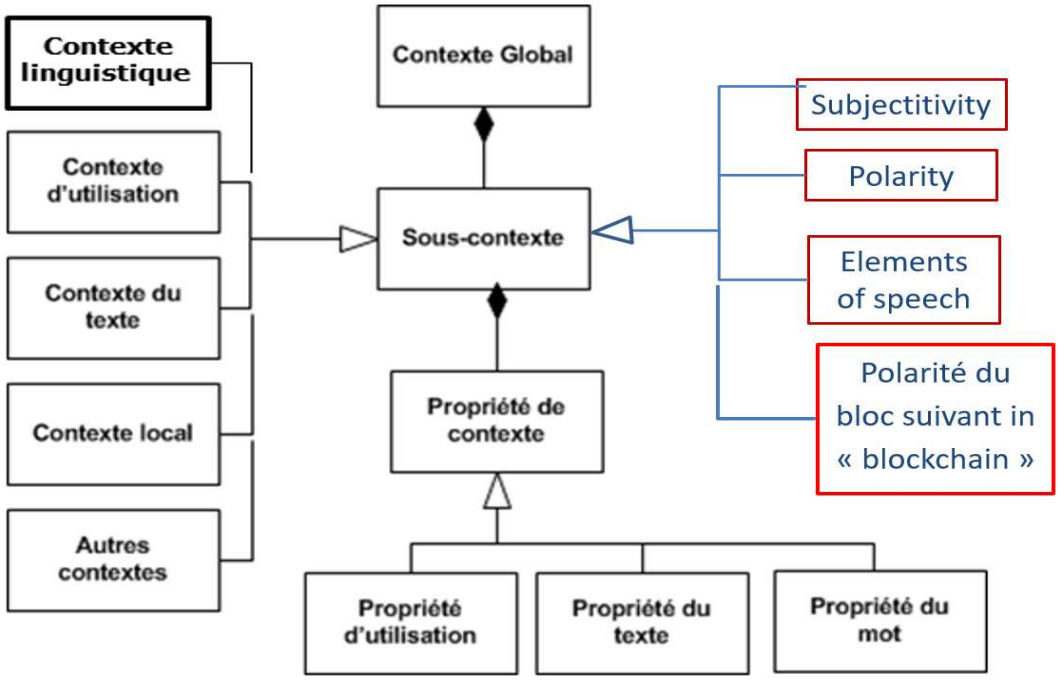
In our approach, innovation consists in associating subjectivity with meaning and not with words to circumvent the problems of ambiguity negatively impacting the calculation of subjectivity and polarity. We have distinguished two phases of analysis, after the disambiguation phase:

- Subjectivity calculation, followed by
- Polarity calculation at an instant t

- Calculation of the prediction at instant t + 1.

Indeed, a subjective word can have different polarities depending on the context. Its meaning can be changed by irony, humor, etc. Disambiguation alone is not enough.

FIGURE 9
DEVELOPMENT OF THE GLOBAL CONTEXT META-MODEL FOR SENTIMENTS PREDICTION IN THE BLOCKCHAIN

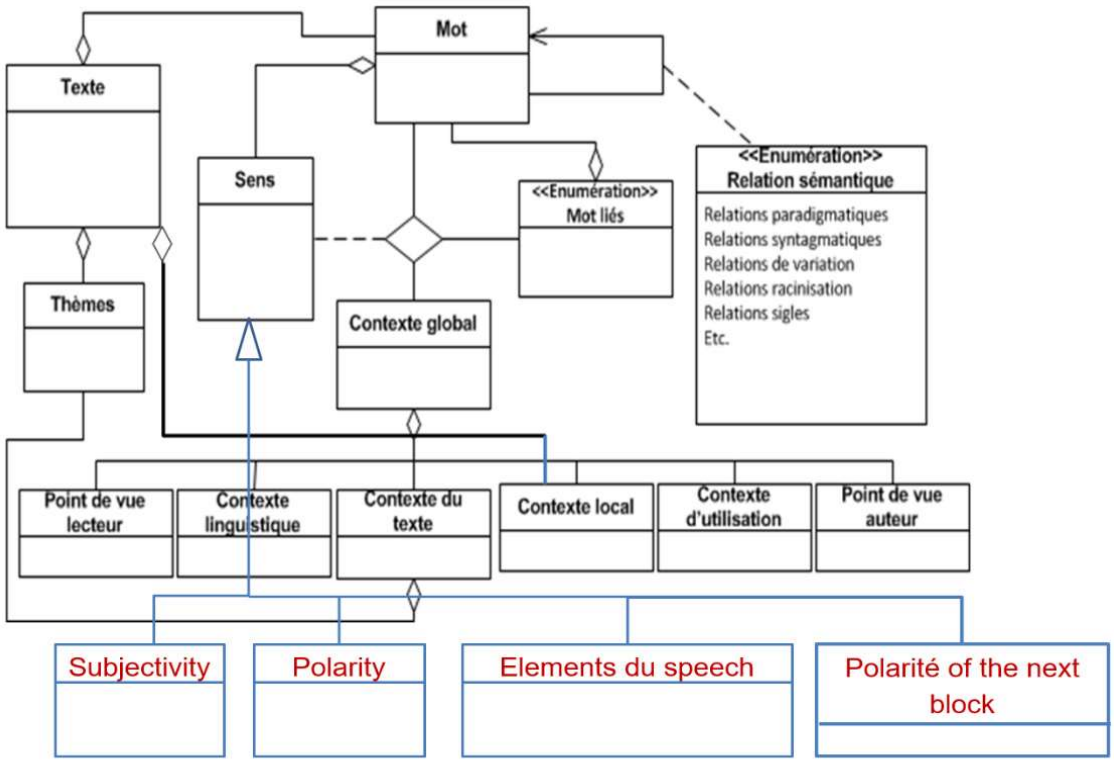


In our approach, dictionaries, correspondence tables and ontologies can be used to model and represent certain elements of the context. We can, for example, use "Mappings" in order to recognize and limit the use of words to a field, to find the complete forms of acronyms and shortcuts or even in order to extract expressions or expressions for specific treatments.

Integrations of Semantic Relations. Since semantic relations are very important in the semantics, we have adopted a model enriched by essential semantic relations. This model will not be detailed in the current article, for more information, see Hammou Fadili 2013.

Semantic Data Model Adaptations. As with natural language, the sentiments analysis and prediction also need the most complete possible representation of a word, of a document (comment, recommendation, etc.), of a corpus, etc.; allowing to collect all the discriminating information to deduce the polarity prediction. Here is a modeled representation of these elements, incorporating several important concepts for the analysis of unstructured data in the service of prediction in BI.

FIGURE 10
AUGMENTED SEMANTIC MODEL OF SUBJECTIVITY, POLARITY, PREDICTION AND ELEMENTS OF SPEECH



This model has the advantage of enriching and extending an existing language model by adapting it to the field of sentiments and opinions prediction. In what follows, we will explain the methods used to instantiate this model; which once, unfolded and instantiated, we obtain an enriched model of instances for machine learning of polarities and predictions.

CONCLUSION & PERSPECTIVES

Sentiment analysis has become a very important discipline in the exploitation of big data. Although there are several proposals and approaches in the literature, there is today no solution which can consider all the requirements of life cycles of sentiments prediction as well as the associated treatments.
It is in this context that we proposed a solution improving the dynamic aspects of the following elements:

- The disambiguation at the beginning of the process
- The context to deduce the global semantics and thereafter the subjectivity and the polarity
- The possibility of ontology integration and other knowledge bases to solve problems such as: acronyms, text messages, expressions (expressions), etc.
- The implementation of an improved LSTM
- Support of intermediate predictions to improve overall prediction
- Learning and correcting predictions thanks to Blockchain
- Guaranteeing the data quality and predictions thanks to Blockchain
- …

Following various tests, we can conclude: the more properties available characterizing the global context for the instances, the more reliable the system is in its predictions. The exhaustive definition and

the extraction of the Characteristics being complex cannot be done without difficulties, several limitations were encountered, and several were abandoned as explained previously. As a reminder, we have:

- Used and abandoned solutions based on descriptions such as ontologies; because they are difficult to set up. In fact, we have been talking about ontologies for several years, but today there are no complete ontologies, except in very limited fields. Therefore, we redirected our work towards unsupervised or mixed solutions for instantiating our extended models.
- Used and abandoned technologies based on "sparse" vector representations; because they cause combinatorial explosions in treatments. We have adopted the "word embeddings" model: new "revolutionary" representations that can be learned from corpus and projected into "semantic" reduced dimensions vector spaces (around 300). This technology was also abandoned in its initial version, because the representations are ambiguous. Therefore, we have improved the latter by training them on the meaning and not directly on words.
- Tested and abandoned several types of algorithms and classifiers, because they did not meet our expectations. Therefore, we adopted and adapted the model of recurrent neural networks (LSTM).

From the current state of progress of the project, it can be said that only part of the problems described above has been treated and solved, the other part constitutes the perspectives for this work. We can recall some of them (those which seem strategic and/or important to us):

- Blockchain technology is very recent, we tried a very first exploitation, deepening its study in order to integrate it more in our processes is a major strategic axis of the perspectives of this work.
- Also, the integration of Blockchain and artificial intelligence seems promising, we have also tried a very first integration of these two technologies of the future. Deepening this study is also another major strategic axis of the perspectives of this work.
- Deepen the study of the characteristics: irony, humour (depending on the culture), metaphor, expressions, etc.; as well as their integration into the process of sentiments analysis and prediction.
- Consider multi-domain and multi-language aspects in sentiments analysis process.
- Implement mechanisms preventing the re-identification of people according to their opinion, comments, etc. many scandals where people have been re-identified from their comments. This question poses an even wider problem on the re-identification of people in Big Data. This is another more important issue of our research.
- Consider nuances of subjectivity which can be expressed through different concepts (Affect, feeling, emotion, and opinion). The distinction between these different aspects and the adaptation of treatments for each constitutes another axis of the perspectives of this work.
- Another perspective concerns the extension of sentiments analysis to other types of data, such as audio and video (multimodal sentiment analysis).
- The integration of the approach in the context of Big Data and its constraints. We have optimized part of the treatments and have dealt with the "unstructured data" and "unavailability/lack" aspects of the processed data, characterizing Big Data, but without considering all its other constraints: acquisition, storage, parallel processing, etc. Taking on all the constraints of Big Data is another perspective of our work.
- Finally, development of a unified system implementing the global "workflow". As explained above, the testing process was done using separate modules and platforms. We therefore envisage the development of other IT modules dedicated to specific tasks, which can be integrated into a single standalone application implementing the entire "Workflow" data processing.

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