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Intelligent Chatter Bot for Regulation Search

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Abstract: This communication presents a functional prototype, named PTAH, implementing a linguistic model focused on regulations in Spanish. Its global architecture, the reasoning model and short statistics are provided for the prototype. It is mainly a conversational robot linked to an Expert System by a module with many intelligent linguistic filters, implementing the reasoning model of an expert. It is focused on bylaws, regulations, jurisprudence and customized background representing entity mission, vision and profile. This Structure and model are generic enough to self-adapt to any regulatory environment, but as a first step, it was limited to an academic field. This way it is possible to limit the slang and data numbers. The foundations of the linguistic model are also outlined and the way the architecture implements the key features of the behavior.

Keywords: Computational Linguistic; Linguistic Reasoning; Natural Language Processing; Text Mining; Chatter bot; Legal Advice; Semantics; Data Mining; Expert Systems

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1 Introduction

During early ’50s, Alan Turing proposed the famous Turing test, one of the main challenges in the Artificial Intelligence field. The test intends to demonstrate the intelligence provided to a computer and, at the same time, the possibility that machines can think in a similar way to humans [1].

J. Weizenbaum continued that idea but from a different perspective, when he built a new program subsequently named ELIZA [2]. ELIZA is not just a computer program, but one of the first prototypes of early Natural Language Processing (NLP). It implements a simple pattern matching as its main strategy for understanding language, but constitutes one of the first conversational robots (chatter bots or chat bots). Some years later Dr. Colby created Parry [6], a chat bot that mimics the behavior of a psychiatric patient suffering paranoia. It emulates responses according to different types of paranoia. Tests showed that a reduced set of psychiatrists were not able to distinguish between the computer and a human patient [3].

Based on ELIZA [2], Richard Wallace developed a new project called Alice (1995) [5]. In doing so, he also developed AIML (Artificial Intelligence Mark-up Language), an application of XML, with a general label named Category that constitutes the elemental unit of knowledge. Every category of knowledge has two components: Patterns and Templates. The pattern is a string of characters representing a dialog, and the template represents the answer to the pattern that is being activated [7].

The PTAH project has a chatter bot as part of the interface to the outside world, which also functions as a smart filter since its filters slang related to regulations and any legal instrument within the academic scope.

It is important to find the proper context of queries to be able to overcome problems like ambiguity, polysemy, anaphora etc. Most of the current solutions are based on approaches known as Natural Language Processing (NLP) [4, 8].

The solution typically involves one or more of the following levels of analysis: phonologic, morphologic, syntax, semantics, and pragmatics, but proposals rarely cover all of them at the same time. This layered approach is use-

ful to break down the problem and make it simpler. Most of the time, there are large dictionaries with certain perprocessing that may be expensive or complex. Usually they become a corpus and require certain degrees of human interaction [9].

There are also many semantic framework (SFW) proposals that complement the previous initiatives, for example: WebODE [10–12]. Such ontological engineering allows the development of web sites to manage certain types of knowledge mostly automatically. Another SFW is ContentWeb, a platform for ontology integration with WebODE that allows the user to interact using natural language but limited to certain slang [13]. That environment interacts with OntoTag (implemented with RDF/S and XML) [14], OntoConsult (an interface for natural language based on ontology) and OntoAdvice (an information retrieval system based on an ontology). Each word receives an URI (Uniform Resource Identifier) as does every new morphosyntactic element.

There are environments to manage morphosyntactics only, for instance XTAG develops fairly good English grammar [15]. It is based on a lexicalization model named Tree Adjoining Grammar (TAG) that generates a grammatical tree to solve the syntax processing. It includes a parser, an X-windows interface and a morphology analyzer.

As a last example, there is a tool for morphology [16] that performs morphological and syntactic analysis with disambiguated segmentation (splits text into segments according to its coherence), special symbol disambiguation (used for sounds not related to words) and error correction for words misunderstood.

This work extends the chatter bot problem, coordinating it with a linguistic model for reasoning in Spanish that leads the text processing from other perspective beside grammar clues. Therefore, it introduces to the chatter bot, some extra technology related to Expert Systems, and semantic distance in a reduced field [23]. That technology was successfully proved in different contexts, automatically managing context in a natural way [24]; specifically it was tested for automatic processing of Spanish dialogs [25].

Here, there is a discretionary morphosyntactic usage but it is pending profiling and feature extraction from historical data using data driven approaches. This way, the framework may be thought of as a layered linguistic reasoning with two steps:

1. The first step is to filter sentences using a linguistic model. Classify the topic automatically using only clues (not semantic explicit by tags, nor structures or dictionaries). Those clues are morphosyntactic schemas previously learnt by an Expert System based on rules.
2. The second step allows a lightweight semantic association at word level using a non-metric distance implementing pre-defined relationships.

This article is organized in the following maner: Section II presents the proposal to the problem of semantic distance related to similarity measurements; Section 3 describes a set of metric distances that may be used instead of the prototype options; Section 4 presents the model PTAH, and the conclusions and future work are described in Section 5.

2 Similarities Measured and Semantics

Searches using similarity have a large number of applications such as image and sound recognition, compression and text searching, computational biology, artificial intelligence and data mining, among others [17]. All of them share the same characteristic: they look for similarities using certain distance or similarity functions predefined for that case. The model most commonly used to represent data being processed is the metric space.

A metric space is defined as a couple (U, d) with U being the objects universe and d: U × U → R+ a distance function defined for U elements that measure the similarity between them. That means the lower the distance the closer the objects are. This function d follows the typical properties for a metric distance:

$$\forall x, y \in U, d(x, y) \geq 0 \quad (positive) \tag{1}$$

$$\forall x, v \in U, d(x, v) = d(y, x) \quad (symmetry) \tag{2}$$

$$\forall x \in U, d(x, x) = 0 \quad (reflexiveness) \tag{3}$$

$$\forall x, y, z \in U, d(x, y) \leq d(x, z) + d(z, y) \quad (triangularinequality) \tag{4}$$

The database is a finite subset of the type X widely included in U with cardinality n. In this model, a typical query implies retrieval of similar objects using searches by certain ranks. Let them be d(q, r) with a query q ∈ U and a

tolerance radius r, a range search is to retrieve all the objects in the database that have a distance less than r from q. This is represented in (eq. 5).

$$d(q, r) = \{x \in X / d(q, x) \leq r\} \quad (5)$$

A search by range can be solved with O(n) distance evaluations when exhaustively examining the Data Base (DB). To avoid that, it is possible to pre-process the DB using an algorithm that builds an index to save time calculation during searching. An indexation algorithm is efficient if it can answer a query using similarity with a minimum number of distance calculations, typically sub-lineal over the number of elements in the DB [18–21]. This project intends to query contents using similarity clues that improve semantic distance and require a lightweight algorithm.

3 Metrics for Distances

The previous metric analysis serves as an introduction to how a good distance metric must behave. Taking that into consideration, it is important to note that distances also strongly depend on the number and quality of the features that make up part of the distances function. Among the most famous distances are the Euclidean and Manhattan [17] but there are many others that are under consideration and evaluation as part of this project. They are depicted below to show the scope of the global project. This part of the research is intended for flexibility evaluation of the model and also to identify how it can be improved. Some of the evaluated metrics were: Overlap Metric (OM), Value Difference Metric (VDM), Metric SFM and Minimum Risk Metric (MRM) [22].

4 The Model and PTAH

a Chatter Bot: this is the input module; a conversational robot coded in Python with patterns in AIML files. It responds to common conversations. From the input sentence, it selects the significant words of the query and removes the “stop words” obtaining a word set.

b Expert System (ES): also implemented in Python as a set of modules that derive the cases and topics. If the word set match a case, it submits the data to the Semantic Association module to search the documents in the Knowledge DB. The ES has a set of rules that outline the use cases of interest. A couple of them are provided in table!1 as examples.

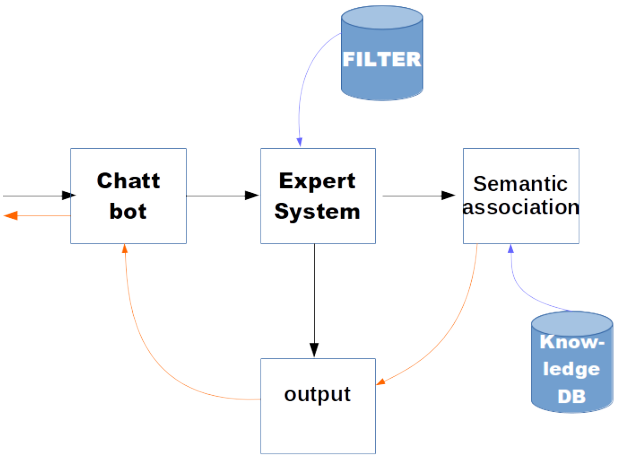

Figure 1: Global architecture of PTAH. There is a connection between the Chatter Bot, the Expert System, the Semantic module and the DB.

Table 1: Detail of use cases and their relation to the ES rules.

ID case	Use case	Rule
11.	¿Qué diferencia hay entre ser docente interino o concursado (ordinario)? What is the difference being transient teacher or regular teacher?	{cuándo |condiciones | diferencia} + {docente | profesor| auxiliar}+ {interino |concursado |ordinario}
13.	¿Cuál son las composiciones de los Consejos Departamental, Directivo y Superior? (How are composed the Department, Directive and Superior Councils?)	Consejo+{Departamental | Directivo| Superior}+ {composición |compuesto | miembros}

These rules are defined syntactically by the following CFG:
<Rule> ::= <AllList>
<Rule> ::= “{“ <ExistList> “}”
<Rule> ::= “word”
<ExistList> ::= <ExistList> “|” <Rule>
<ExistList> ::= <Rule>
<AllList> ::= <AllList> “+” <Rule>
<AllList> ::= <Rule>

Then, rules are composed by words joined by “+” or “|” and grouped by “{“ and “}”. AllList are lists where all the components must be part of the query. ExistList represents components where at least one of them must be part of the word set. Words are compared by similarity using Levenshtein Edit Distance.

If the distance is less than a radius, there is a match. We built an interpreter to check each rule against the word set and return the summation of the minimum distances that match the rule. A word set can match 0 or more rules ordered by distance.

If there is no match, the chatter bot use their AIML files to respond. Otherwise, the expert system sends the matching rules to the semantic association module.

c Semantic Association Module: implemented as a set of stored procedures in PostgreSQL, its goal is to look for documents that have semantic similarity to the word set of the rule. Each rule has an optimized array, indexed by word keys that represent the existence or not of the word key in the rule. Each document has a similar array with the frequency of the word keys in that document.

According to the model, the reasoning is represented by the following algorithm (semantic distance function):

1. Find Meta data(data)
2. Find Binary vector(Meta data)
3. Retrieve binary vector using:
3. Bias A: restriction for no divergence
3.1. Binary vector from every bylaw
3.2. Relative frequency for every word (w) in the bylaw $\rightarrow$ freq(w)
3.3. MIN(w)= argMIN{ freq(w)}
3.4. MAX(w)= argMIN{ freq(w)}
3.5. find weighting for every w: p(w)=1/freq(w)
3.6. p(w)=1/(MAX(w)*1.05)
3. Bias B: relevance in the current case
3.1. Binary vector(ID-case)
3.2. NUM(w)= number of words in ID-case
3.3. Let p'(w_i) = 1/NUM(w_i) for every w_i
3. Bias C: relevance in the current context
3.1. Binary vector(query(data))
3.2. For every w_i(Meta data) and every ID-case:
3.2.1. IF w_i(Meta data) AND w_i(ID-case) AND match (ID-case) scoring(ID-case)+= p'(w)
3.2.2. IF w_i(Meta data) AND w_i(ID-case) ~match(ID-case) scoring(ID-case) += p'(w) * 0.95
3.2.2. ELSE scoring(ID-case) - =p'(w) /* there is no w_i(ID-case) in knowledgeDB */
3.3. select argMAX{scoring(ID-case)}
3.3.1. IF number-of(ID-case) >1 THEN ID-caseBEST=select argMAX{freqH(ID-case)}
3. Bias D: hit precision in the DB
3.1. Search KnowledgeDB (binary vector(ID-caseBEST))
3.2. IF(hit (ID-caseBEST)) -> scoring += p(w)
3.3. IF(~hit(ID-caseBEST) -> scoring += p(w) * 0.95
3.4. ELSE /* there is no w_i(ID-case) in knowledgeDB */
3.4.1. IF hit(w_i(ID-case))-> scoring - = p (w)
3.4.2. IF ~hit (w_i(ID-case))-> scoring - = p' (w)
3.5. Output (select * from KnowledgeDB where argMAX {scoring})

In the algorithm, freqH represents the previous usage frequency, compiled during the entire model's history.

d Knowledge DB: this is implemented over a PostgreSQL Data Base Management System. It is composed of a Documents table and an Articles table. One document can have 0 or more articles. Each article has an array of frequencies of word keys associated.

The DB is populated with textual information of the regulation, but the data loading is expected to improve using an OCR to include non-textual documents.

We have already performed the first batch of experiments to determine the Precision and Recall of the system. Due to the restrictions of this short communication, we are not able to include these preliminary results.

5 Conclusions and Future Work

This paper presents a linguistic reasoning for dialogs, compatible with the indirect semantic approach presented by models using morphosyntactic but augmented with data-driven heuristics. The PTAH prototype implements that model extending the traditional processing for chatter bot using new layers of abstraction that do not fit in the traditional strategies of NLP.

Those layers distribute filters among a rule-based ES with the following explicit steps:

Bias A: restriction for no divergence
Bias B: relevance in the current case
Bias C: relevance in the current context
Bias D: hit precision

It is important to note that this does not require labeling, dictionaries or a trained corpus. From preliminary results, it can be seen that Precision and Recall metrics are fairly good even though the distance metric is poor and that these can be improved with better distance functions.

The current pending tasks are as follows:

- Add dictionaries and historical data to improve query results.
- Self-tuning of the rules in the ES. Also the rules could be learnt probabilistically from history.
- Evaluate other metric distances that may evidence linguistic relationships between words. This would improve newer situations and make the system more flexible.
- Evaluate the precision and recall with a higher number of queries.
- Evaluate the same parameters using the distances in section III.
- Implement a new module for OCR and automatic loading of the DB.
- Improve the interface using a synthesizer and a voice recognition system. This could make the interaction more friendly.
- Extend the use cases to other topics improving the chatter bot to be less sensitive to slang and dialects.
- Enhance the ruled system with Fuzzy Logic.

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